Profiling Movement and Gait Quality in Children's Physical Activity

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1.1 Abstract

There is a paucity of research demonstrating objective methods to empirically derive quality of movement measurements and its subsequent relationship to health, performance and risk factors. Therefore, the overarching aim of this thesis was to characterise and profile children's physical activity movement (and gait) quality.

Following laboratory based work to confirm the feasibility and development of assessing movement quality in children, ankle mounted accelerometers were used for all experimental studies. Classic and novel temporal and frequency domain analyses were conducted in all studies. All data underwent hierarchical clustering based on normalised Euclidean distances. Further inferential statistics were conducted to investigate differences and correlations, accordingly.

Experimental chapter 1 consisted of three smaller studies to, first, test the technical specifications of the SlamTracker accelerometer and that the data output were valid and reliable. Second, to verify the validity of using raw accelerometry to estimate movement characteristics during ambulation compared to gold standard methods, and third, to characterise the relationship between overall integrated acceleration and three-dimensional kinematic variables whilst performing fundamental movement skills. The accuracy, suitability and validity of the SlamTracker raw accelerometer data (absolute variance: <0.001 g, CV: 0.004%, in all axes) was confirmed. Following this, the ability to accurately capture complex movement characteristics, compared to gold standard methods, such as joint angle (r=0.98, P=0.001) and force production (r=0.98, P=0.001) was demonstrated. Finally, there were no differences found in overall activity (integrated acceleration) in children who completed the same fundamental movements, whilst a large variance was detected in the kinematics of children's movement (CV: up to 65%). We concluded that quality of movement, whilst evidently important and diverse even in standardised tasks, needed a specific operational definition in the context of this thesis. Following pilot work, the term quality was therefore defined as, and derived from, the purity of the fundamental frequency spectra (signal) during human movement, specifically relating to gait, otherwise termed, spectral purity.

Experimental chapter 2 was necessary to establish a credible base for the combination of raw accelerometry and novel analytics, outside of laboratory settings. This was the first empirical study to draw upon frequency domain analysis and hierarchical clustering in the characterisation of movement in children. The aims of this study were; first, to characterise the movement quality of children during a standardised fitness assessment and second, to report how movement quality characteristics cluster according to body mass indices in 9-11y children. One hundred and three children (10.3±0.6y, 1.42±0.08m, 37.8±9.3kg, body mass index; 18.5±3.3 $kg \cdot m^2$) volunteered for this study, had anthropometric recordings taken and took part in the twenty-metre multistage fitness test. This study found that children with high BMI had significantly lower spectral purity and time to exhaustion. Moreover, BMI was hierarchically clustered with stride profile, and time to exhaustion was clustered with spectral purity. BMI was negatively correlated with time to exhaustion, spectral purity, integrated acceleration, stride angle and stride variability. In conclusion, spectral purity was representative of children's performance during a standardised fitness test, and significantly negatively correlated with body mass index.

Experimental chapter 1 and 2 both utilised more controlled environments, whereas *Experimental chapter 3* moved away from controlled into more free-form, uncontrolled movement, i.e. recess. The aims of this study were to characterise children's recess physical activity, and investigate how movement quality characteristics cluster during school recess. Twenty-four children (18 boys) (10.5±0.6y, 1.44±0.09m, 39.6±9.5kg, body mass index; 18.8±3.1 $kg{\cdot}m^2$) who were a representative sub-sample of 822 children (10.5±0.6y, 1.42±0.08m, 27.3±9.6kg, body mass index; 18.7±3.5 $kg{\cdot}m^2$), took part in a normal school-time recess for one school week (five days). This study found that integrated acceleration (overall physical activity) during recess was invariant day-to-day, yet significant daily differences were found for spectral purity. Integrated acceleration was clustered with spectral purity, in addition to a significant positive correlation between integrated acceleration and spectral purity (P<0.05), whilst body-mass index percentile was negatively correlated with integrated acceleration and spectral purity. This study highlighted that movement quality measurement was achievable and robust in an uncontrolled environment (i.e. recess). Given the link established in previous chapters between spectral purity and movement quality, the tenuous literature on motor competency development through childhood, and, the evidence motor competence may track though the life course; it was deemed appropriate to examine movement quality characteristics in early years' children, in conjunction with traditional motor competency assessment.

The aims of *Experimental chapter 4* were two-fold; to characterise children's free-play physical activity and investigate how movement quality characteristics cluster in children (3-5y). Sixty-one children (39 boys, 4.3±0.7y, 1.04±0.05m, 17.8±3.2kg, body mass index; 16.2±1.9 $kg{\cdot}m^2$) took part in free-play and completed the movement assessment battery for children, second edition, using standardised procedures. There were significant differences between motor competency classifications for spectral purity and integrated acceleration (P<0.001). Spectral purity was hierarchically clustered with motor competence and overall physical activity. Additional significant positive correlations were found between spectral purity, integrated acceleration and motor competence (P<0.001).

In conclusion, children's movement quality can be reliably computed using novel analytics in laboratory and in-field. The novel quality measure coined in this thesis, spectral purity, was shown to be hierarchically clustered with, and indicative of, performance, physical activity and motor competence. This thesis has expanded the current evidence base on children's physical activity and movement quality and demonstrated that raw accelerometry can be used, in conjunction with novel analytics, to provide innovation in movement quality assessment across ages.

1.2 Summary of publications

Clark, C. C. T., Barnes, C.M., Stratton, G, McNarry, M.A., Mackintosh, K.A., Summers, H.D. (2016). A Review of Emerging Analytical Techniques for Objective Physical Activity Measurement in Humans. *Sports medicine* [epub. ahead of print]. In-print: March 2017, 47 (3), 439-447.

Clark, C. C. T., Barnes, C.M., Holton, M.D., Summers, H.D., Stratton, G. (2016). Profiling Movement Quality and Gait Characteristics According to Body-Mass Index in Children (9–11 y). *Human movement science*, 49, 291-300.

Barnes, C. M., **Clark, C. C. T**., Holton, M.D., Stratton, G., Summers, H.D. (2016). Quantitative Time-Profiling of Children's Activity and Motion. *Medicine and science in sports and exercise*, 49(1), 183-190 (collected study data, assisted in writing, analyses and revision of the manuscript).

Clark, C. C. T., Barnes, C.M., Holton, M.D., Summers, H.D., Stratton, G. (2016). A Kinematic Analysis of Fundamental Movement Skills. *Sport Science Review*, 25(3-4),261-7.

Clark, C. C. T., Barnes, C.M., Holton, M.D., Summers, H.D., Stratton, G. (2017). SlamTracker Accuracy under Static and Controlled Movement Conditions. *Sport Science Review*, 25(5-6), 321-344.

Clark, C. C. T., Barnes, C.M., Holton, M.D., Summers, H.D., Mackintosh, K.A., Stratton, G. (*in press*). Profiling movement quality characteristics of recess activity in 9-11-year-old primary school children. *Human Movement Science*.

1.3 Declarations and Statements

1. I, Cain Craig Truman Clark, hereby declares that the work presented in this thesis has not previously been accepted in substance for any degree and is not being concurrently submitted in candidature for any degree.
2. I, Cain Craig Truman Clark, hereby declares that the thesis is the result of my own investigations, except where otherwise stated and that other sources are acknowledged by footnotes giving explicit references and that a bibliography is appended.
3. I, Cain Craig Truman Clark, hereby gives consent for the thesis, if accepted, to be available for photocopying and for inter-library loan, and for the title and summary to be made available to outside organisations.

Signed: ______________________________ (candidate)

Date: ________May 2017________

1.4 Contents page

1.5 Acknowledgements

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To my supervisor, Professor Gareth Stratton, you are a remarkable and prolific researcher and friend, whose knowledge, care, attention, support and whit knows no bounds. You always knew when to provide a stern word, encouragement, informative feedback, pastoral support or to just be a friend. The completion of this thesis and all related work is a result of your incomparable guidance. It has been an honour to work with you and a source of immeasurable pride informing people that my PhD supervisor is *The* Gareth Stratton. I also wish to thank Dr Kelly Mackintosh and Professor Huw Summers for sharing your intellect, insight, and above all, your time. I sincerely could not have completed this thesis without your help and guidance.

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specifically, hopefully there will be plenty more things posted on *ResearchGate* for you to read…

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1.6 List of tables, figures, equations

1.6.1 Tables

1.6.2 Figures

1.6.3 Equations

1.7 Abbreviations

α_{max}	-	Stride angle
°	-	Degrees
^{18}O	-	A natural, stable isotope of oxygen
^{2}H	-	Deuterium (also known as heavy hydrogen) is one of two stable isotopes of hydrogen
3D	-	Three-dimensional
AAP	-	American Academy of Paediatrics
ACOS	-	Inverse of cosine
Activity count	-	A dimensionless unit of accelerometer output related to the
		intensity of physical activity
ANN	-	Artificial neural network
A_{radial}	-	Radial axis
ASD	-	Autism spectrum disorder
ATAN	-	Inverse of the tangent
BMI	-	Body mass index; weight (kg) divided by height (m^2)
CDF	-	Cumulative distribution function
Children	-	Primary school aged: 5-11y, whilst the

		experimental chapter specifically refers to 9-11y
CO_2	-	Carbon dioxide
COM	-	Centre of mass
CV	-	Coefficient of variation
CVA	-	Cerebro-vascular attack
d	-	Euclidean distance
D1	-	Absolute difference in frequency
D2	-	Absolute difference in stride angle
DC	-	Direct current
DLW	-	Doubly labelled water
Early years	-	Refers to infants aged 3-5y
EE	-	Energy expenditure
EF	-	Elbow flexion
ELM	-	Extreme learning machine
ER	-	External rotation
FFT	-	Fast Fourier Transform
F_{MAX}	-	Maximum impact force generated upon foot strike
FMS	-	Fundamental movement skills
FSR	-	Force sensitive resistor
G	-	Gravity
Gauss	-	Magnetic field
GMM	-	Gaussian mixture model
HMM	-	Hidden Markov model

Hr	-	Hour
HR	-	Heart rate
Hz	-	Frequency (per second)
IC	-	Indirect calorimetry
ICC	-	Intra-class coefficient
IOTF	-	International Obesity Task Force age- and sex-specific BMI thresholds for classifying overweight and obesity in children and youth aged 2-18 years
IR	-	Internal rotation
Kcal	-	Kilocalories
KG	-	Kilogram
KJ	-	Kilojoules
KM	-	Kilometre
KNN	-	*k*-nearest neighbour
L	-	Litre
LDA	-	Linear discriminant analysis
LQ	-	Lower quartile
Med	-	Median
MEMS	-	Micro-electromechanical system
MET	-	Metabolic equivalents classification
Min	-	Minute
MJ	-	MilliJoules
mL	-	Millilitre

MM	-	Millimetre
MPH	-	Miles per hour
MRV	-	Maximum radial velocity
MSB	-	Multi-sensor board
MSFT	-	Multi-stage fitness test
MVPA	-	Moderate to vigorous physical activity
N	-	Number
NW	-	Normal weight
O_2	-	Oxygen
OB	-	Obese
ODBA	-	Overall dynamic body acceleration
OW	-	Overweight
P	-	Statistical measure that denotes significance
PA	-	Physical activity
PCA	-	Principal component analysis
PPA	-	Physiological profile assessment
Q	-	Stride profile quotient
R or R^2	-	Reliability coefficients; statistical measures that express correlation between two measures
SA	-	Stride angle
SD	-	Standard deviation from the mean
SF	-	Stride frequency

SIN	-	Sine
SP	-	Spectral purity
SV	-	Stride variability
SVM	-	Support vector machine
TTE	-	Time to exhaustion
UQ	-	Upper quartile
UW	-	Underweight
VEDBA	-	Vector of the dynamic body acceleration
$\dot{V}O_2$	-	Oxygen consumption; expressed in absolute terms ($L \cdot min^{-1}$) or relative to body mass ($ml \cdot kg^{-1} min^{-1}$)
$\dot{V}O_{2MAX}$	-	Maximum oxygen consumption; expressed in absolute terms ($L \cdot min^{-1}$) or relative to body mass ($ml \cdot kg^{-1} min^{-1}$)
Y	-	Years

2.0 Introduction

2.1 Rationale and background

Physical inactivity is the largest contributor to risk factors for non-communicable diseases in the world [1-3]. Conversely, physical activity has been identified as an integral contributor to a healthy lifestyle [4] and can provide numerous health benefits [5]**,** including decreased risk of premature death by around 30% for those attaining the recommended levels of physical activity on most days of the week (see [1,2]). Whilst these data are not available for children, the systematic reviews of Saunders, et al. [6], Chaput, et al. [7], Carson, et al. [8] and Poitras, et al. [9] have quantified the relationship between physical activity, sedentary behaviour, sleep and health and concluded that these behaviours are co-dependent and all related to health risk [10]. A sedentary lifestyle, common during childhood, adolescence and continued into adulthood, is a major concern for the health of the general public [2,11] and the substantial increase in the prevalence of overweight and obesity and other non-communicable diseases, such as diabetes, cancer, hypertension and cardiovascular diseases over the previous decades [12,13], is partly attributed to lower levels of physical activity and increase in sedentary behaviour [14]. There are numerous acute physiological and psychosocial benefits to physical activity among children and adolescents and, second, that physical activity behaviours between childhood and adulthood are correlated and that physically active children are more likely to grow up to be physically active adults compared with their inactive peers [15,16]. It is therefore advocated that physical activity be promoted amongst children and adolescents for health enhancement and to embed lifelong behavioural patterns that will result in more active adult populations in the future occur [10,15-17].

There is a dearth of research demonstrating objective methods to empirically derive movement quality measures and as such, this thesis intends to explore novel measures of movement quality that underpin movement. Authors, such as Bellanca, et al. [18] and Brach, et al. [19], have demonstrated quality measurements in specific population are useful and valid using raw accelerometry. Furthermore, in geriatric patients and Parkinsonian gait, respectively, frequency domain analyses can reliably highlight deteriorating gait characteristics [20,21]. To date, almost all focus on physical activity has been on time spent above or below various thresholds, such as moderate-to-vigorous physical activity. There has been no integration of physical activity quantities and qualities. Quality is a nebulous term, and can have connotations relating to psychology, physiology, biochemistry, well-being, emotional state, biomechanics or even life. For the purpose of this thesis, the term 'quality' shall be referred to as, and derived from, the purity of the fundamental frequency spectra (signal) during human movement, specifically relating to gait, and will be explored throughout the experimental chapters of this thesis.

In a seminal study, Stodden, et al. [22] proposed a theoretical model that explains the interaction between the development of motor competence and physical activity. Whilst Stodden, et al. [22] suggested that motor competence is the underlying mechanism that will influence physical activity engagement levels across the life course, measures to support this assertion are lacking. In early childhood, current modes of motor development assessment find there is no relationship between motor development, health related fitness and physical activity, and motor competencies are naturally variant [22-24]. During middle to late childhood and beyond, individuals with a higher motor competence begin to demonstrate increased health-related fitness compared to that of a child with lower motor competence, using traditional assessments [25,26]. Whilst the relationship between physical inactivity, unhealthy weight and motor competence has been investigated [27-30], the underlying mechanisms of this correlation are yet to be understood. Robinson, et al. [31] reported that a positive relationship exists between motor competence and physical activity throughout childhood, motor competence may be both a precursor and a consequence of weight status, and that the strength of these (dis)associations increases from childhood and adolescence into adulthood. Despite the emerging evidence base of motor competence correlates in adolescence and beyond, there exists little no adequate measures of motor competence and movement qualities in early years and pre-adolescent children, and therefore necessitates development [32].

Whilst accelerometers are the *de facto* standard in objectively measuring physical activity, literature has focussed on quantifying activity in the form of activity counts or time spent above or below activity thresholds, as opposed to the movement qualities [33,34]. Furthermore, functional limitations, such as high frequency movement and noise information escaping the bandpass filter, which in turn adds unexplained variation in activity counts [35], variations in epoch length, cut points and device type further add to the lack of clarity in the literature [36-38]. This is further confounded by the consensus that commercially available accelerometers only provide manufacturer-dependent output values that are computed by unpublished and proprietary signal processing techniques, resulting in a unit of measure termed ‘activity counts’. Activity counts summarize data in an epoch, reducing the burden of data management, analysis, and interpretation; [34,39] however, as traditional accelerometers are limited in memory and battery capacity to store raw signal data, data processing stages are performed on the device itself, and this process is irreversible once the count has been stored in local memory. This irretrievable conversion prevents re-analysis of the raw accelerometer signal using novel analytics and data processing techniques however, information about the raw accelerometer signal is irretrievably lost and a full picture of physical activity quality overlooked. This irretrievable conversion prevents re-analysis of the raw accelerometer signal using novel analytics and data processing techniques [40,41].

On the other hand, accelerometers that store the raw signal for each movement can be analyzed in the frequency domain using Fourier analysis and subsequently assess gait and movement quality in-field [18,20,42,43]. This type of analysis is highly suggestive of a fundamental feature of the neural control of movement [44] and can be further processed using clustering algorithms. Cluster analysis is an analytic procedure that reduces complex multivariate data into smaller subsets or groups. Compared with other data reduction methods, such as factor analysis, clustering yields groupings that are based on the similarity of whole cases, as opposed to the individual variables that comprise those cases [45]. Cluster analysis represents a valuable analytic tool for the health and exercise sciences and may be used for profiling, or in the development of classification systems or taxonomies [45,46]. However, this has not been applied to children’s movement in any age group.

2.2 Problem statement

Across the literature, there exists a dearth of research examining the gait movement quality of the multi-dimensional construct, physical activity. The devices and analytical techniques available for application to physical activity data has proliferated beyond traditional methods of assessment and analysis, therefore novel approaches to characterise and assess physical activity warrants extensive investigation. For the purpose of this thesis, the operational definition of “children” shall refer to the age range of 5-11y, whilst “early-years” shall refer to the age range 3-5y.

2.3 Thesis aims

The overarching aim of this thesis was to characterise and profile children's physical activity movement and gait quality.

Experimental chapter one: the aims of this chapter were to; quantify the mean, standard deviation and variance of a raw accelerometer at a range of speeds, to verify the validity of using raw accelerometry to measure force (N) and ankle angle (°) during ambulation, to characterise the relationship between facets of fundamental movement, and finally, to characterise the relationship between overall integrated acceleration and three-dimensional kinematic variables whilst performing fundamental movement skills.

Experimental chapter two: The aims of this chapter were first, to apply automated, novel analyses to characterise the movement quality of children during the MSFT [47-49], and second, to report how movement quality characteristics of gait cluster according to body mass indices.

Experimental chapter three: The aims of this chapter were to characterise the recess activity of children aged 9-11y using novel methods and investigate day-to-day variability of novel characteristics of recess.

Experimental chapter four: The aims of this chapter were to characterise children's free-play physical activity and, investigate how movement quality characteristics of gait cluster with free-play and motor competence in children (3-5y).

3.0 Literature Review

3.1 Physical activity and health

Physical inactivity is the largest contributor to risk factors for non-communicable diseases worldwide, whereas engaging in regular physical activity is widely recognised to counteract this [1-3]. Physical activity has been identified as an integral contributor to a healthy lifestyle [4,6] and can provide immediate and future health benefits [5,16,50]. Strong relationships exist between physical activity and health, with higher physical activity levels leading to reduced risks of coronary heart disease [51], hypertension [52], non-insulin dependent diabetes mellitus [53], stroke [54], colon cancer [55], osteoporotic fractures [56] and depression [57]. Further, physical activity has also been frequently associated with improved physiological functioning and lower disease risk according to observations drawn from controlled experimental trials and population-based epidemiological studies [58] There is sufficient empirical evidence to conclude that physical activity has beneficial effects on adiposity levels, blood pressure, plasma lipid and lipoprotein levels and non-traditional cardiovascular risk factors (inflammatory markers, endothelial function and heart rate variability) in adolescents and adults [16,59-62]. Moreover, physical activity has beneficial effects on several components of mental health (self-concept, anxiety and depression) [5,13]. The benefits of regular physical activity have been clearly set out across the life course [1,2].

4.1.1 Physical activity guidelines

It has been recommended that children (5-17 years) should accumulate at least 60 minutes of moderate intensity physical activity each day [2,63,64], whilst for early years children (3-5 years) it is recommended that at least 180 minutes of physical activity is achieved every day (Department of Health [65], Department of Health and Aging [66], Tremblay, et al. [67]). Recently, however, a step change was made in relation to physical activity guidelines. The Canadian 24-Hour Movement Guidelines for Children and Youth were the first to address the whole day [10,68]. The Canadian 24-Hour Movement Guidelines for Children and Youth encourage children and youth to “Sweat, Step, Sleep and Sit”. For optimal health benefits, children and youth (aged 5–17 years) should achieve high levels of physical activity, low levels of sedentary behaviour, and sufficient sleep each day. A healthy 24 hours includes: uninterrupted nine to 11 hours of sleep per night for those aged 5–13 years and eight to 10 hours per night for those aged 14–17 years, with consistent bed and wake-up times; and an accumulation of at least 60 minutes per day of moderate to vigorous physical activity (MVPA) involving a variety of aerobic activities. Vigorous physical activities and muscle and bone strengthening activities should each be incorporated on at least three days per week; several hours of a variety of structured and unstructured light physical activities; no more than two hours per day of recreational screen time; and limited sitting for extended periods. Preserving sufficient sleep, trading indoor time for outdoor time, and replacing sedentary behaviours and light physical activity with additional moderate to vigorous physical activity can provide greater health benefits [10,68]. The rationale behind these changes were drawn from a series of comprehensive reviews (see: Saunders, et al. [6], Chaput, et al. [7], Carson, et al. [8] and Poitras, et al. [9]).

Poitras, et al. [9] supported the notion that children and youth accumulate at least 60 minutes per day of moderate to vigorous physical activity for disease prevention and health promotion [1]. Following a systematic review, Poitras, et al. [9] reported that total physical activity was positively and significantly associated with physical, psychological/psychosocial, and cognitive health indicators [10,68]. Relationships were more consistent and robust for higher-intensity compared with lighter-intensity physical activity, whilst light-intensity physical activity was positively associated with cardiometabolic biomarkers. The findings highlight the potential benefits of both light intensity physical activity and total physical activity, neither of which were captured in the previous guidelines [9]. A further review, by Carson, et al. [8], into sedentary behaviour found that higher durations and/or frequencies of screen time and television (TV) viewing were associated with adverse body composition; frequency and time spent TV viewing was associated with higher cardiometabolic risk; TV viewing and video-game use were associated with adverse behavioural indicators; greater time spent reading and homework were associated with higher scholastic achievement; screen time was associated with lower cardiorespiratory fitness; and screen time and computer use were associated with reduced self-esteem [8]. Screen time has a stronger relationship with health indicators compared with overall sedentary time, and concluded that less sedentary behaviour (especially screen time) was associated with better health indicators [8]. A systematic review on the effect of sleep, by Chaput, et al. [7], noted longer sleep duration was linked with positive indicators of adiposity, emotional control, scholastic achievement, and overall health and well-being [7]. Chaput, et al. [7] concluded that shorter sleep duration is congruent with detrimental physical and mental health outcomes. Finally, Saunders, et al. [6] reported that school-aged children and youth having a high physical activity, high sleep, low sedentary behaviour had better measures of adiposity, cardiometabolic health and general health indicators [6]. Whereas those who had low activity and sleep also had deleterious health indicators [6]. Collectively, the systematic reviews of Saunders, et al. [6], Chaput, et al. [7], Carson, et al. [8] and Poitras, et al. [9] provided an evidence base and led to the inception of the 24-hour movement guidelines, targeting a more holistic approach than previously seen. This presents a paradigm change representing a fundamental shift from focusing on behaviours in isolation, to the composition of behaviours across a whole day [6-9]. Consideration for all behaviours along the movement spectrum as a collective is necessary and warranted, and holds promise in the promotion of population health [10].

3.1.2 Childhood physical activity

In children and young people (5-18 years of age) there is evidence of the beneficial effects of physical activity on musculoskeletal health, cardiorespiratory fitness, several components of cardiovascular disease, adiposity, and blood pressure [5,28,69,70]. Further physical activity can improve children's psychological well-being and promote moral reasoning, positive self-concept, and social interaction [71]. Thus, physical activity and fitness in childhood are associated with numerous health benefits [14,72], and should be promoted [73]. Further, in the late 1980's, Blair, et al. [74] hypothesised a number of relationships that linked childhood activity to adult health, and adult activity. Specifically: (i) childhood physical activity influences adult physical activity, which may affect adult health, (ii) childhood physical activity has a direct beneficial effect on child health, which predicts adult health and, (iii) childhood physical activity has a direct beneficial effect on adult health, this hypothesis has since been supported in the literature [5,16].

Higher levels of physical activity in children are associated with improved cardio-respiratory fitness and muscular strength [75], enhanced bone health and reduced body fat [76]. Participation in physical activity is vital for enhancing children's physical, social, cognitive and psychological development [76]. Further, children who frequently participate in physical activity demonstrate reduced symptoms of anxiety and depression, and improved self-esteem and confidence [76]. Whilst children's activity has been widely investigated, the pre-school period (3 to 5 years of age) is often overlooked, yet pre-school represents a crucial period of development whereby the regulation of energy balance is programmed [77]. For example, lifestyle behaviours are thought to track from pre-school to childhood, and subsequently into adulthood [78,79], indicating that this is a critical time for promoting physical activity and preventing sedentary behaviours [80]**.** On the other hand, the relationship between physical activity, sedentary behaviour and health in the early years is not fully understood and warrants investigation [81]. Pivotal to the research is an accurate measure of physical activity that should go over above current approaches [32]. In addition, diversification and refinement on the approaches to measuring physical activity will enable better understanding of these relationships [82]. There has been much debate in the literature into whether young children are sufficiently active for health [83], and conflicting conclusions have been reached. One solution to the dearth of understanding throughout development (i.e. physical activity, motor development and control interaction), is to assess elements of movement quality, as well as quantity.

3.2 Motor development

In a seminal study, Stodden, et al. [22] proposed a theoretical model that explains the interaction between the development of motor competence, physical activity participation and weight management. Stodden, et al. [22] suggested that motor competence is the underlying mechanism that will influence physical activity engagement levels. However, the model asserted that physical activity is also mediated by age, perceived motor competence, physical literacy, health related fitness and obesity risk [22]. During early childhood, the cognitive capability to accurately perceive motor competence is not sufficiently developed [23,84]. However, when children reach middle to late childhood their cognitive ability will have developed to the point they compare themselves to their peers [23,84], resulting in a stronger relationship between motor competence and perceived motor competence. Children who have a higher perceived motor competence and higher motor competence will perceive tasks to be easier and are more likely to engage in physical activity, whereas the reverse is evident in children with low actual and perceived motor competence [85].

Based upon the findings of a comprehensive review, Robinson, et al. [31] reported that a positive relationship exists between motor competence and physical activity across childhood, the strength of associations between motor competence and both cardiorespiratory endurance and muscular strength/endurance increase from childhood into adolescence. Finally, motor competence has tenuously been shown to be both a precursor and a consequence of weight status and demonstrates an inverse relationship across childhood and adolescence [31]. Whilst some literature has explored the impact youth physical activity levels have through the life course, there exists little more than tenuous links between early years and childhood motor competence, tracking across the life course. Therefore, adequate measures of motor competence and movement qualities are required to explore this further [32].

3.3 Physical activity, fundamental movement and body-mass index

Fundamental movement skills (FMS) are considered the basic building blocks for movement and provide the foundation for specialized and sport-specific movement skills required for participation in a variety of physical activities. Fundamental movements skills can be categorized into locomotor (e.g., run, hop, jump, leap), object-control (e.g., throw, catch, kick, strike), and stability (e.g., static balance) skills [86]. Current tools to assess FMS, such as the movement ABC test and the gross motor development test, assume that the reliability data and validity information is well founded [87]. However, there is not sufficient evidence that clearly indicates the FMS test items are actually evaluating the motor skill constructs [88]. Test-retest and inter-rater reliability has been reported in the literature to range anywhere between 0.49 to 1.00 [89-91].

In-spite of reliability issues, there is strong evidence to suggest a positive association between fundamental movement skill competency, physical activity and health related benefits in children [24,92-94]. Many cross-sectional studies have shown a linear relationship between FMS and physical activity. However, cross-sectional data cannot determine causality, for example, it is not clear if FMS influences physical activity, or if physical activity influences FMS. In a systematic review on FMS in children and adolescents Lubans, et al. [92] found that FMS was associated with organised and non-organised physical activity and pedometer step counts although ten studies were cross-sectional hindering cause and effect conclusions. Okely, et al. [95] found that as little as 3% of organised physical activity was predicted from FMS levels (r^2 =0.03) in 13-16 years old adolescents, whilst Hamstra-Wright, et al. [96] reported that 29% of the variance in locomotor skills was accounted for by organised sport, which is a much higher percentage of variance than reported in the other studies (3% for Okely, et al. [95]; 10.4% for McKenzie, et al. [97]; 3.6% for Barnett, et al. [98]; 19.2% for Cliff, et al. [99]).

Previous research has highlighted that FMS is inversely correlated with weight status [100-103] and out of the 21 studies cited in the Lubans, et al. [92] systematic review, nine of them used body mass/BMI as a variable to compare FMS mastery. Six of the nine studies highlighted a significant inverse relationship between weight status and FMS mastery. Okely, et al. [95] also established that overweight and obese children score lower in the locomotor skills (run, gallop, skip and hop). McKenzie, et al. [97] on the other hand did not find a significant relationship between childhood FMS scores and adolescent physical activity levels, although an inverse relationship between FMS and weight status was identified. The theory is that improving FMS at an early age will result in increased PA and improved health. This is an important concept given that excess body weight is correlated with low physical activity levels, increased all-cause mortality risk and biomechanical movement perturbations [104,105]. It has been shown that children with excess weight move less and with much greater difficulty than normal-weight counterparts [105-110], and the impact of excess body mass in children appears to hinder physical activity, movement quality and fundamental movement skill [22,24]. The compromised movement in overweight children is attributed to greater force through joints, decreased mobility, modification of gait pattern, and changes in the absolute and relative energy expenditures for a given activity [105,108]. Furthermore, overweight children have a longer gait cycle and stance phase duration as well as a reduced cadence and velocity compared to normal weight [111-113]. The difficulty overweight children have in adapting to different walking speeds is disadvantageous when participating in physical activities involving frequent speed changes, including standardised fitness tests [108]. Spatiotemporal and kinetic analyses of obese vs. non-obese children showed that obese children were mechanically less efficient than normal weight children, i.e. obese children used more mechanical energy when walking at the same speed, compared to normal weight children [108].

3.4 Physical activity and energy expenditure

A multitude of instruments providing objective measures of physical activity have been developed, the simplest being pedometers [114], which allow the estimation of distance walked and associated energy expenditure [115,116]. Whereas, other sensors and methods, including; accelerometers, heart rate monitoring, doubly labelled water, and direct observation have been employed to objectively quantify physical activity and its related energy expenditure [117,118].

Doubly labelled water is classified as the gold standard of energy expenditure measurement, however, this technique does not measure specific physical activities, *per se*, but rather estimates total energy expenditure over a period from which the physical activity energy expenditure can be calculated [119]. This method uses non-radio-labelled isotopes of oxygen and hydrogen (^{18}O and ^{2}H) administered as a standard dose of water at the start of the measurement period (usually 7-21 days). The ^{18}O is eliminated from the body in CO_2 and water and the ^{2}H is eliminated as water only. The difference between the elimination rates of each isotope is an estimate of CO_2 production over the measurement period and the total energy expended during the measurement period can then be calculated using a standard equation [120]. Physical activity energy expenditure can then be calculated by subtracting dietary induced thermogenesis and resting energy expenditure from total energy expenditure [120]. However, physical activity is a complex multidimensional human behaviour that encompasses all bodily movement from fidgeting to marathon running [121,122]. Consequently, it is important to understand the relationship between specific physical activities and energy expenditure. Types of physical activity may be spontaneous (i.e., daily life activity), obligatory (i.e., activity necessary for survival) or voluntary (i.e., formal, planned exercise) [123]. The major contributor to daily physical activity energy expenditure in children is spontaneous physical activity [124] . There is evidence that low levels of physical activity are associated with increased risk of weight gain and this in turn may have health consequences for children [5,16,50,125], hence why the focus of physical activity literature has been on energy expenditure.

Physical activity is a multi-faceted construct and can be expressed and quantified in numerous ways. For example, physical activity can be described according to context, such as surrounding environment and social conditions and further characterised according to type, frequency, duration and intensity [126]. The type or modality of physical activity (recreational, obligatory or occupational, aerobic or anaerobic, continuous or intermittent, weight-bearing or non-weight bearing) refers to the specific activity in which the individual is engaged. The frequency of physical activity refers to the number of bouts of physical activity over time, whilst duration is the length of time in each activity bout. The dose of physical activity, however, may be expressed according to absolute or relative intensity. Absolute intensity is the actual rate of energy expenditure over a specified time period and is generally expressed as oxygen uptake ($\dot{V}O_2$; $L{\cdot}min^{-1}$), oxygen uptake relative to body mass ($ml{\cdot}kg^{-1}min^{-1}$) and/or energy expenditure ($kcal{\cdot}min^{-1}$, $kJ{\cdot}min^{-1}$, MJ, $kJ{\cdot}kg^{-1}$). Absolute intensity can further be described according to multiples of resting energy expenditure using the metabolic equivalents classification (MET). METs are defined as the ratio of energy expended from work to resting metabolic equivalent (3.5 mL of $O_2{\cdot}kg^{-1}min^{-1}$) or 1 $kcal{\cdot}kg^{-1}hr^{-1}$. Knowing the MET value associated with a particular type of activity and individual body mass permits the energy cost of the activity to be estimated [127,128].

The Compendium of Physical Activities was conceived in 1993 and subsequently revised in 2000 and currently presents MET values for 605 specific activities for adults, categorized under 21 major headings [128,129]. The values range from 0.9 METs (sleeping) to 18 METs (running at 10.9 mph). MET values are used to express the intensity of physical activity according to intensity categories (i.e., light, moderate, vigorous). Although absolute intensity levels corresponding to MET values exist for children, research is equivocal over which are most appropriate. In most studies, moderate intensity is defined as ≥3 METs. It is asserted by some that a threshold of ≥5 METs is more suitable for children [130,131]. More recent evidence suggests ≥4 METs is an appropriate threshold for describing ≥moderate intensity activity in children [130,131].

Accelerometers can record movement in the anterior-posterior, medio-lateral and vertical directions, provide an alternative method of estimating EE in a free-living environment and are considered the *de facto* standard for objectively measuring physical activity. Physical activity EE can be predicted from the anterior-posterior direction of an accelerometer signal [132], whilst the vertical acceleration is most sensitive to a majority of activities like walking or running. The signal integral of triaxial acceleration outputs have been shown to have linear relationship with the metabolic EE [133]. Commercial accelerometers follow the same principles and convert raw acceleration signal into activity counts over an epoch. The activity counts represent the estimated intensity of measured activities during each time period and subsequently compared with the DLW method [134] or indirect calorimetry to estimate the EE [135].

A review of physical activity measurement reported that 63% of monitoring devices used were accelerometers, predominantly the ActiGraph [136], whilst literature has focussed on quantifying activity in the form of activity counts, time spent above or below activity thresholds or energy expenditure, as opposed to the movement qualities [33,34]. Furthermore, functional limitations, such as; high frequency movement and noise information escaping the bandpass filter which in turn adds unexplained variation in activity counts [35], variations in epoch length, cut points and device type further add to the lack of clarity in the literature [36-38].

3.5 Physical activity and recess

Children spend a significant proportion of their waking time at school. Non-curricular time, such as school recess periods (recess and lunch break) and after-school programs, provide opportunities for children to be physically active within the school environment [137,138]**.** Of these contexts, recess periods may provide the single greatest opportunity during the school day to impact on child physical activity levels [109,139,140]. However, in recent years there has been a trend to reduce the frequency and duration of school recess, or remove it from the school day altogether, often due to academic pressures [138,141]. Consequently, it is important that school recess is included in school-based physical activity programming and policy, and that the recess environment is conducive for children to make physically active choices [142]. Whilst the scheduling and duration of recess periods vary between countries, social and physical environments that facilitate enjoyable and safe physical activity engagement in this context would be advantageous [143]. A number of reviews have examined correlates of preschool, children's and adolescents' physical activity [144-146], yet these have predominantly focused on factors associated with whole-day activity. Since physical activity is a multidimensional behaviour influenced by numerous factors across several domains [147], it is logical to also consider specific contexts in which children and adolescents are active. This notion links to a conceptual model proposed by Welk [148], where the author addressed the area of motor competence. Welk [148] categorized the five most commonly reported determinants/correlates of physical activity into (1) personal, (2) biological, (3) psychological, (4) social, and (5) environmental, and the available literature supports this assertion. Welk [148] suggests in his conceptual model that biological factors such as physical skills and fitness act as enabling factors that are promoted by physical activity with increased fitness and competence, leading to increased adherence to physical activity and subsequent enhancement of perceived and actual competence.

Ridgers, et al. [146], conducted a systematic review into correlates of physical activity during recess and reported that age, grade level, BMI, cardiovascular fitness, outdoor environment, physical education provision, and number of recess periods had no association with recess physical activity [149-151]. The authors went on to summarise a number of significant, positive associations with physical activity during recess, which included; playing ball games, being male, perceived encouragement, loose equipment and overall facility equipment [151-153]. Current research indicates that many correlates of recess physical activity are equivocal, indicating that more empirical research is required [146]; for example, special educational needs, supervision, socioeconomic status, fixed equipment, playground markings, season, temperature, weather, organized activities and recess duration all affect recess activity to varying levels [146].

Whilst an appreciation must be also made for the differences between primary (3-11y) and secondary (12-16y) school aged children. Factors consistently reported to significantly influence primary school aged physical activity levels include; sex (being male), parental overweight status, parent support physical activity preferences, intention to be active, perceived barriers (inverse), previous physical activity, healthy diet, program/facility access, and time spent outdoors [146,154-158]. Whilst commonly reported factors significantly associated with secondary school aged physical activity are; sex (being male), ethnicity (white), age (inverse), perceived motor competence, depression (inverse), previous physical activity, community sports, sedentary time (inverse), and parent support, highlighting that in older age groups (adolescents vs children) social and mental health/well-being factors increase in their influence, whilst biological factors remain constant [146,154-158].

A further consideration is that a range of physical activity measures have been used to assess physical activity levels, which has a profound influence on the identified associations. While the majority of child studies reported in Ridgers, et al. [146] utilised objective measures to quantify physical activity during recess, (such as accelerometry and direct observation), aspects such as device type, model type, accelerometer cut-points and observation systems have varied widely, thereby hindering many of the observations [146]. Furthermore, self-report measures are well documented to be less accurate [159]. Therefore, future research should explore how movement quality indicators may be used, in conjunction with traditional quantitative measures i.e. energy expenditure, overall activity counts [32], and to characterise and profile children's physical activity movement and gait quality.

3.6 Physical activity quality

A contemporary problem that needs addressing is a clear definition of 'quality' in a physical activity context. Whilst quantity, with reference to physical activity, is well described, with the most common definition coming in form of the razor coined by Casperson, et al. [160]; "Physical activity is defined as any bodily movement produced by skeletal muscles that results in energy expenditure", the term 'quality' is nebulous and can have connotations relating to; physical activity, movement, psychology, physiology, biochemistry, well-being, emotional state, biomechanics or even life.

Quality can be used to describe an individual's overall self-assessment or subjective appraisal of well-being or life satisfaction associated with physical status and functional abilities, mental health, happiness, satisfaction with interpersonal relationships and economic and/or vocational status [161,162]. For children and youth, there is the additional domain of school/academia [161]. Health-related quality of life includes aspects of overall quality of life that are directly related to physical and/or mental health [161,162] As such, health related quality of life reflects the degree to which a person is able to participate physically, emotionally and socially with or without assistance [163].

Social interactions and participation can also be described in terms of quality. Full social participation is considered a fundamental human need, with empirical evidence finding that lack of social connections increases the odds of death by at least 50% [164]. The quality of multidimensional tenets of social relationships have been reported to increase odds of mortality by 91% among the socially isolated [164]. The magnitude of this effect is comparable to that of other known risk factors of mortality, such as obesity or physical inactivity [164,165]. In humans of all ages, deficits in social relationship quality, such as social isolation or low social support can similarly lead to chronic activation of immune, neuroendocrine, and metabolic systems that lie in the pathways, leading to cardiovascular, neoplastic, and other common aging-related diseases [166-169].

Objectively-measured biomarkers of physical health, such as C-reactive protein, systolic and diastolic blood pressure, waist circumference, and body mass index can be used to indicate physiological quality [170,171]. For instance, blood pressure may be used to determine the quality and efficiency of the myocardium’s ability to distribute and regulate blood flow [170,171]. Physiological quality may also refer to a molecular and cellular level and the capability to perform basic cellular functions. All cells perform certain basic functions essential for their own survival. These basic cell functions include, but are not limited to: nutrient retention, chemical reactions, waste removal, protein synthesis and reproduction [170,171]. If any cell within the human system does not perform these basic, and subsequent specialized, functions then the quality of the cell would be considered compromised.

Quality can also be referred to in the context of gait and has been determined using raw accelerations, aligned to anatomical axes with respect to gravity [172-174] and analysis of the bipedal (left-to-right leg) symmetry [175-177]. Quality can be determined from bouts of locomotion and described as; vertical trunk displacement [178-180], stride frequency, and walking speed [178-180]. Whilst gait quality can be described in terms of; intensity, expressed as the root mean square of the signal; variability expressed as stride-to-stride variability in walking speed, stride frequency and length; symmetry expressed as the harmonic ratio [181,182]; smoothness expressed as the index of harmonicity [183]; and complexity expressed as the mean logarithmic rate of divergence per stride using Wolf's method [184] and sample entropy [185]. Further examples include; the autocorrelation at the dominant period [174], the magnitude and width of the dominant period in the frequency domain [186-188] and the percentage of power below 0.7 Hz [189]. However, authors, such as Bellanca, et al. [18] and Brach, et al. [19], have demonstrated that quality measurements in specific populations can be derived from analysing the fundamental frequency and harmonic content of movement. With the addition of raw accelerometry, novel analytics, such as fast Fourier transformation (FFT), has been used to process the accelerometer signal and identify gait qualities; walking smoothness, walking rhythmicity, dynamic stability and stride symmetry [18,19]. For the purpose of this thesis, the term 'quality' shall be referred to and derived from the fundamental frequency spectra (signal) during human movement, specifically relating to ambulation, using a raw accelerometer and will be explored throughout the experimental chapters of this thesis.

3.7 Application and accuracy of novel analytics

Signal processing of accelerometer data has moved beyond the descriptive approach of simply quantifying overall activity using time spent in thresholds or counts per minute. There are more substantive insights that will take the accelerometer data past the descriptive stage that characterises the data, allowing both quantity and quality to be reported [114,117]. Chen, et al. [117] reported that sensor type and data processing will directly impact the results of the outcome measurement. Further, that multisite assessment and combining accelerometers with other sensors and new analytics will offer additional advantages. Yang, et al. [114] reported that the application of sensors is expanding to encompass, for example, characterisation of falls, postures and gait qualities. Both, Chen, et al. [117] and Yang, et al. [114], respectively, highlighted issues with traditional analyses, such as device reliability, insensitive energy expenditure algorithms, epoch length affecting overall physical activity and inability to detect intermittent activities. Future technological improvements will necessitate examining raw acceleration signals and developing advanced models for accurate energy expenditure prediction and activity classification [114,117,190].

Recently, emerging approaches to physical activity measurement have focused on prevention of falls, postural movement, energy expenditure and analysing raw accelerometry traces [191,192]. One example, pattern recognition, which is an analytical technique used to classify activity behaviours (such as jumping, walking or running) can make use of data from several sensors placed on the body. This process involves gathering data from participants carrying out a protocol of structured activities and then processing the signal for common features. Once processed, it is possible to program a computer to detect features in data collected from participants carrying out defined activities, otherwise known as machine learning. The algorithms used to do this depend largely on the features used for classification of activities and subsequent variants of these. In addition to machine learning and pattern recognition, mathematical modelling has resulted in improved energy expenditure estimations, by incorporating accelerometry, heart rate monitors, indirect calorimetry (IC) and anthropometric data. Further the utilisation of more sophisticated techniques, such as artificial neural networks, can feed data information through the network, and then compute to better predict energy expenditure or movement [193].

The diversification of analytical techniques to characterise physical activity is accelerating, and multiple, diverse platforms on which to assess and report physical activity have come to the fore, and therefore an updated synthesis of the current evidence base is warranted. Further, consideration of accuracy and associated limitations is also needed to indicate the current suitability of different techniques.

3.7.1 Reviewing method

Literature search

A computerised search was conducted using the following databases; Web of Science, PubMed and Google Scholar. A combination of the following key words was used to locate studies for review, post January 2010; ‘physical activity’, ‘pattern recognition’, ‘wearable motion sensor’, ‘artificial neural network’, ‘energy expenditure’, ‘sensor’, ‘multi sensor’, ‘monitor’, ‘motion sensor’, ‘accelerometer’, ‘accelerometry’, ‘regression’, ‘hidden Markov model’ and ‘machine learning’. Terms were combined such that every search included one term related to; ‘physical activity’ and one term related to type; ‘measurement’ or ‘classification’. Figure 1 shows the results of the literature search and article selection process.

Study characteristics

Multiple searches were then made in each of the selected databases and additional searches for relevant references and citations linked to the studies obtained during this primary search were conducted. The selection process sought to identify studies that assessed physical activity using emerging analytical techniques, of varying study design, conducted human-based investigations, assessed the accuracy of analytical technique [114,117].

Study selection

Coding of papers only allowed for studies that adopted emerging analytical techniques for physical activity measurement, including; pattern recognition, artificial neural networks, hidden Markov models, machine learning and regression, and assessed technique accuracy. Studies of varying designs were acceptable for the purposes of this review; however, technical reports, review articles, non-human based studies, or studies which did not measure activity or report technique accuracy were not considered further. Following the selection of appropriate articles, study design, aims, population, analytical technique, overall accuracy and limitations were reviewed in Table 1.

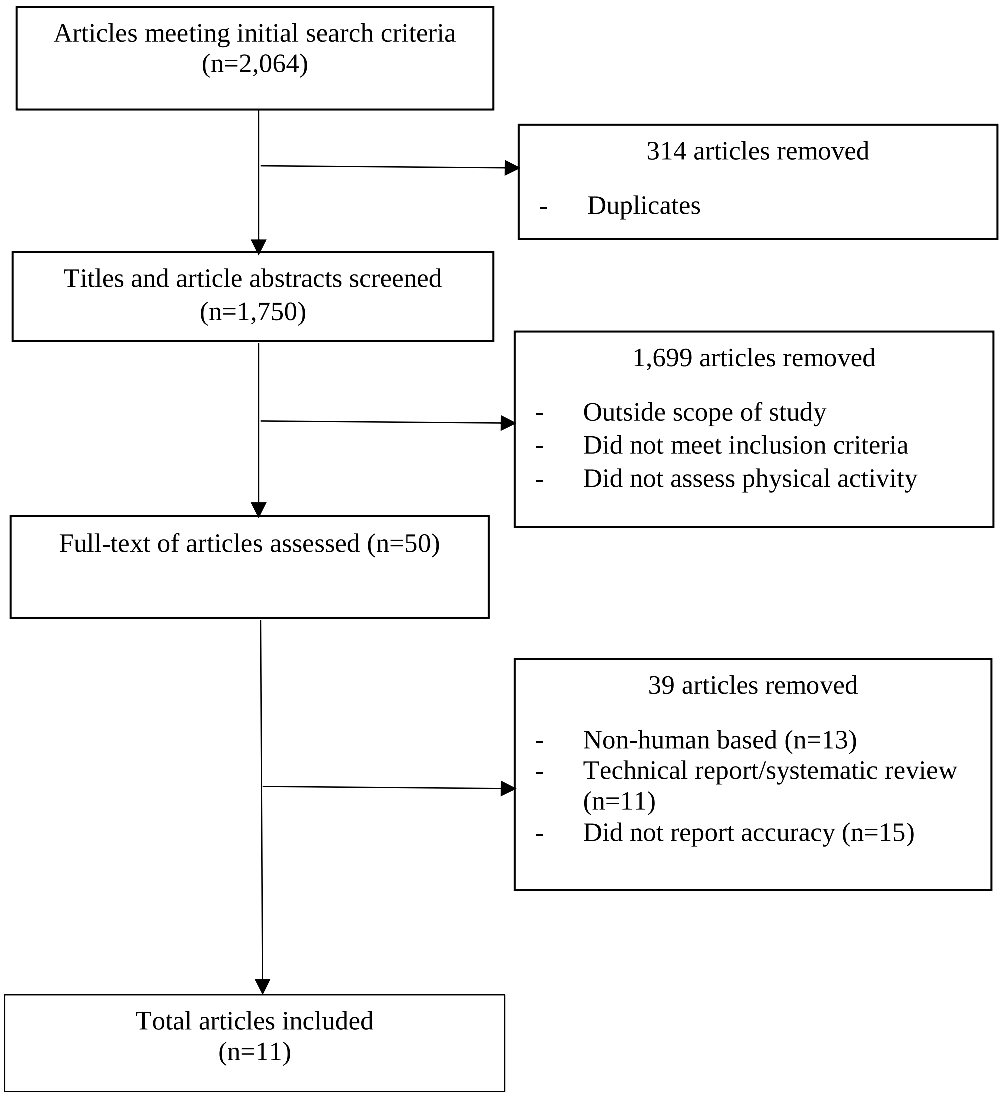

Figure 1. Flowchart of the search and selection process.

3.7.2 Results

The electronic search subsequently identified 2,064 potentially relevant articles. Following screening and detailed assessment, 11 studies were deemed suitable for review. Of the 11 studies included, one study utilised linear discriminant analysis, four utilised feature extraction and machine learning, two utilised a support vector machine classifier, one utilised dynamic time warping, one utilised hierarchical clustering, one utilised an extreme learning machine, and one utilised a hidden Markov model. Table 1 summarises; study aims, participant characteristics, study outcomes, overall accuracy and study limitations.

Table 1. Emerging technique accuracy (including falls, activity type, behaviour, prediction).

Study	Aim	Population[a]	Instrument/technique	Overall accuracy	Conclusion	Limitations
Aziz, et al. [194]	To develop and evaluate the accuracy of wearable sensor systems for determining the cause of falls.	Nine males and three females (20-35y)	Accelerometer (MicroStrain), linear discriminant analysis.	89%	These results establish a basis for the development of sensor-based fall monitoring systems that provide information on the cause and circumstances of falls, to direct fall prevention strategies at a patient or population level.	All falls were performed under controlled laboratory conditions by healthy individuals between the ages of 20 and 35, who fell on soft gymnasium mats. So application to real world setting needs to be investigated. Small sample and biased towards males.
Bulling, et al. [195]	To investigate eye movement analysis as a new sensing modality for activity recognition	Six males and two females (23-31y)	Electrooculography (Mobi8), feature extraction and machine learning, SVM.	76.1%	Activity recognition using eye movement analysis can be used to successfully recognise five office based activities and has future potential	Some subjects had to be excluded due to poor signal quality. Any pathologic eye disorder (such as nystagmus) can significantly affect activity recognition
Duncan, et al. [196]	To examine the accuracy of a MSB that infers activity types (sitting, standing, walking, stair climbing, and running) and estimates EE	25 males and 37 females (39.2±13.5y)	MSB, accelerometer (Actical), stationary calorimetry (TrueMax), HR monitor (Polar), feature extraction.	97% (laboratory) and 84% (field).	The MSB provides accurate measures of activity type in laboratory and energy expenditure during treadmill walking and running.	Device underestimates EE when used in the field. Device estimates EE based on walking speed and does not factor in events such as carrying loads.
Fulk, et al. [197]	To determine the ability of a novel shoe-based sensor that uses accelerometers, pressure sensors, and pattern recognition with a SVM to accurately identify sitting, standing, and walking postures in people with stroke.	Two males and six females (60.1±9.9y) who suffered a cortical CVA 51.7±45.1 months prior	Force sensitive resistors (Interlink), SVM.	99.1% to 100% individual models. 76.9% to 100% group models.	The combination of accelerometer and pressure sensors built into the shoe was able to accurately identify postures	There was no attempt to examine the ability of the sensors to detect transitions such as sit to/from stand position or ascend/ descend stairs
Goncalves, et al. [198]	To determine stereotypical motor movements for application to individuals with ASD	Two participants	Xbox Kinect sensor, dynamic time warping algorithm	100%	Results were promising, some aspects need to be improved, i.e. noise of the depth image that can lead to false-positives in the identification, and improve the accuracy of the application when the user sits too far from or too close to the Kinect sensor.	Subjects used did not suffer from ASD. No participant information. Hand flapping was the only movement. Did not correctly identify duration of movement.
Kjaergaard [199]	To identify multiple human movement (flocking) derived from multiple sensors.	16 participants	WiFi, accelerometer, compass, hierarchical clustering.	87%	Hierarchical clustering improves flock recognition and multiple sensors improve recognition compared to uni-model approaches	No participant information was provided.

Leutheuser, et al. [192]	To generate a publicly available benchmark dataset for the classification of daily life activities, comparing multisensor based classification to state-of-the-art algorithms	13 males and 10 females (27±7y)	Wearable sensor (SHIMMER; 3axial accelerometer and 3axial gyroscope combination), feature extraction and machine learning.	89.6%	The comparison showed that the proposed data fusion of accelerometer and gyroscope provided a useful tool to distinguish between complex activities like ascending stairs.	Inconsistent sensor placement and numbers used for different algorithms.
Mannini, et al. [200]	To investigate machine learning methods for classifying human PA	20 participants	Accelerometer. HMM	92.2 to 98.5%.	The use of HMM with pattern recognition is a promising approach for the future.	Only basic motions captured. No sex or age information.
Trost, et al. [201]	To develop and test ANNs to predict PA type and EE from processed accelerometer data	100 participants (11.0±2.7y)	IC (Oxycon), accelerometer (Actigraph), ANN	81.3% to 88.4%.	ANNs can be used to predict both PA type and EE in children and adolescents using count data from a single waist mounted accelerometer	Authors noted that EE can be predicted accurately from a limited number of activities. ANNs developed from laboratory controlled activities not PA or free living conditions. No sex information provided.
Xiao, et al. [202]	To develop a wearable feedback system for monitoring the activities of the upper-extremities	6 participants (29.7±4.4)	FSR, ELM classifier	92%	Results support the use of this system for providing instant feedback during functional rehabilitation exercises.	Only discrete postures were used. No sex information provided.
Zhang, et al. [203]	To extract and evaluate PA patterns from image sequences captured by a wearable camera	One participant	Wearable camera, good features detector	>85%	Many types of PA can be recognized from field acquired real-world video	Extremely low sample size, camera position was not securely fixed. No participant information reported.

Table I definitions; ANN: Artificial neural network, ASD: autism spectrum disorder, CVA: cerebro-vascular attack, EE: energy expenditure, ELM: extreme learning machine, FSR: force sensor resistor, HMM: hidden Markov model, HR: heart rate, IC: indirect calorimetry, MSB: multi-sensor board, PA: physical activity, SVM: support vector machine. [a] Age data are mean ± SD, or range.

3.7.3 Discussion

Accelerometry based studies

Several studies applied emerging analytical techniques with accelerometry to assess physical activity, with a range of accuracies and limitations (see: Table 1). Measuring human physical activity using wearable monitors [191,192] demonstrates promising results. Physical activities, including walking, running, cycling and rope jumping, have been accurately (up to 100% accuracy in certain circumstances) classified using sensors with multiple inputs (for example accelerometers or gyroscopes) [192,197]. Aziz, et al. [194] successfully measured physical activity and sedentary behaviour using accelerometers in older adults or those with impaired ambulation using linear discriminant analysis, which is a type of machine learning, with overall accuracy of up to 89% in classifying fall type. Further, computed values were highly correlated to walking speed prediction (r=0.98). However, problems arose when using the same approach in highly transitory activities and when detecting falls that were a result of syncope. Leutheuser, et al. [192] also utilised machine learning, in combination with feature extraction, and could correctly identify basic daily life physical activities with 89.6% accuracy. The use of machine learning with accelerometry appears to allow identification of specific movements with high accuracy. However, at present activity classification using this method appears to only be able to identify basic movements. Conversely, when focussing more broadly on inferring activity type, and not specifically falls or basic movement, Duncan, et al. [204] achieved 97% accuracy during walking and running in the laboratory and 84% accuracy in the field (performing scripted activities including walking up and down stairs, walking around and picking up a 20-pound object), using feature recognition. This particular method appears to be successful due to the incorporation of EE in order to infer activity type, rather than the accelerometer signal alone. However, once in field testing was performed, the accuracy falls by 13 percentage points, indicating reliability issues outside of a controlled setting. Trost, et al. [201] advocated the use of a different form of machine learning, ANN, and reported high accuracy (88.4%) in activity classification. This type of machine learning has been applied to multiple settings with high levels of accuracy and reliability and relies on a computational model inspired by natural neurons to process and link inputted data [205]. Trost, et al. [201] was the only study to have utilised a substantial sample size, giving strength and reliability to their findings. Although accelerometers can be combined with novel analyses for the same or similar outcomes, there are numerous mathematical processes and models that can be applied under the umbrella of machine learning, i.e. ANN, feature detection, linear discriminant analysis, all of which demonstrate comparable level of accuracy. In addition to machine learning approaches, pattern recognition in combination with accelerometry has demonstrated very good reliability. Mannini, et al. [200] reported that very high accuracy (92.0 – 98.5%) could be achieved when classifying postural (sitting, lying and standing) and basic motor movements (stair climbing, walking, running and cycling) when applying a HMM to characterise an accelerometer signal. This indicates that when pursuing activity classification, machine learning and pattern recognition represent two very promising techniques. At present, these techniques are limited to classifying only simple or basic movements and as such, further work is required to extend these models to be applicable in a more generalised setting. Further, a confounding limitation of emerging analytics in conjunction with accelerometry is that the number of participants used in studies has been small (Fulk, et al. [197], Leutheuser, et al. [192]). It is evident that studies have addressed varying problems, ranging from pedestrian flocking, to falls, or more predominantly, inferring activity and the relative accuracies of these techniques has been shown to be very high.

Other sensor based studies

There have been a number of approaches used to classify characteristics in physical activity data, such as pattern recognition, machine learning and principal component analysis (PCA) [200]. When analysing a raw accelerometry trace, it is very difficult to deduce what action has been performed without any other input or prior knowledge about the actions. In such cases, a pattern recognition technique, such as a HMM, may be applied, where observations are available (the raw accelerometry trace) but the background information giving rise to those observations are ‘hidden’ (prior knowledge of any activities or movement). Therefore, HMM is an approach used to classify features in a dataset. Other statistical modelling approaches can be used where the probability data derived from a ‘training set’ of data are used to classify some features into various motion and physical activities. An important consideration when classifying data is that large datasets will result in multiple features and characteristics, which results in time-consuming data analysis and collection. Artificial neural networks, in addition to decision trees, have also been used to good effect [206,207]. Further, pre-processing and reclassifying data can help reduce the dimensionality of large data sets [200], and using novel analytics can help to compute the meaningful basis in a data set by filtering out noise, resulting in improved accuracy [200]. However, a consistent feature associated with many pattern recognition analytics is that many data need to be gathered in order for patterns to be recognised. This can be time-consuming and expensive and requires significant computer memory and power [200]. Further, whilst accelerometry has become the *de facto* device for objectively assessing physical activity, the use of other sensors (i.e. cameras, force sensitive resistors, electrooculography) to achieve the same outcome has grown. It is evident that the aim of many emerging analytical techniques has been to aid in better detecting the quality and type of activity that a person is undertaking. Zhang, et al. [203] incorporated motion cameras to recognise patterns of movement and concluded that basic motor movements could be recognised with 85% accuracy. The accuracy reported by Zhang, et al. [203], using a pattern recognition approach, was lower than Mannini, et al. [200]. This could be an artefact of the device, as acquired images are often blurry and ineffective in capturing feature points. However, this approach attained similar levels of accuracy to Trost, et al. [201]. Goncalves, et al. [198] utilised an Xbox Kinect camera in conjunction with a pattern recognition approach, dynamic time warping, where the similarity between patterns which may vary with time of different durations is measured [198]. The authors reported success in application of the technique, however, the gesture sensing algorithm was only applied to two participants and one action, hand flapping. So, although the accuracy reported was absolute, there is still much development needed in order to apply this to more movements. Bulling, et al. [195] reported an accuracy of 76% when identifying activities such as text copying, reading a printed paper, taking hand-written notes, watching a video, and browsing the web. The authors contended that recording the movements of human eyes, electrooculography, can successfully be used to identify certain activities and may be feasible in wider applications, such as accurately identifying non-traditional activities (e.g. rock climbing), which would be missed by common sensing modalities. However, further investigations would be required to corroborate the effectiveness of this technique.

The application of cameras, in different forms, to characterise activity type has demonstrated variable success when complemented with novel analyses. A further example of instruments used when attempting to characterise human movement with novel analytics is force sensitive resistors. Fulk, et al. [197], for example, mounted the device in the footwear of participants to measure plantar pressure and record the acceleration signal, thereby inferring postural activity in stroke victims. The raw signal from the device was analysed using a support vector machine, which is a supervised machine learning technique that can use training examples to learn the dependencies in the data (in Fulk, et al. [197], the computer learns how the signals from the sensors can predict postural activities) and apply the learned model to recognition of previously unseen data [197]. Across eight participants, accuracy in identifying postural activity of 99-100% was found, indicating that, using a modest sample size, the combination of acceleration and pressure traces, postures may confidently be assessed. Similar to Fulk, et al. [197], Xiao, et al. [202] utilised a force sensitive resistor, but applied it to the upper extremities to analyse force myographic signals of the forearm. The authors were able to accurately identify upper extremity movements during a controlled drinking task (92% accuracy). Xiao, et al. [202] also utilised a form of machine learning to learn and classify the data, an extreme learning machine classifier. As with previously mentioned studies, a training approach was taken, where the ELM classifier was 'taught' or 'trained' to model the force myography trace.

Although substantial gains have been made utilising emerging analytics to develop deeper insights into human physical activity data, the underlying algorithms require further development. It is evident that when simple postural changes or activities are quantified, there are a number of techniques and instruments that can be used to accurately determine them, which is not the case when complex or specific activity recognition is required. The main problem with the studies reviewed is that they are predominantly laboratory based, or have much lower accuracy in-field, use small sample sizes and are exploratory. Many of these studies also failed to account, or indeed report, anthropometric and physiological metrics such as age, sex and fitness, which could conceivably affect patterns of movement.

Cluster analysis

Whilst refining emerging techniques should remain a strong focus, so that adequate levels of accuracy and confidence may be established and improved upon, the techniques by which physical activity can be measured will continue to proliferate. Cluster analysis involves the use of algorithms to separate a population into clusters or groups based on various parameters, such as activity behaviours, and has been identified by Kjaergaard [199] to have high accuracy. Kjaergaard [199] focussed on group activity, rather than individual activity, using flock detection and found by incorporating accelerometry, Wi-Fi and cluster analysis that pedestrian flocks could be correctly identified and tracked with 87% accuracy. One problem encountered in this study was flock proximity (i.e. the ability of the cluster analysis to successfully differentiate between flocks was encumbered when different groups become entwined or were too close), thereby indicating that the mathematical modelling process needs further refinement. The cluster analysis approach relies upon an iterative process of interactive, multi-objective optimization and may be used in various ways depending on which parameters are applied. For example, cluster analysis can be used to determine friendship groups in the playground or could be used to determine trends and correlations between factors such as physical activity, age and socioeconomic status. Cluster analysis is versatile and has previously been used to study animal behaviours and movements theory [208] and in biology to identify and track cells [47]. Given the nature of human behaviour, cluster analysis could be of great use in advancing the analysis of physical activity indices.

Conclusion

Research into physical activity is expanding to incorporate a multitude of different techniques, and within each approach exists a series of limitations that need addressing. This chapter identified that a range of emerging analytical techniques have reported high accuracy across physical activity measurement, with success in postural activity classification. However, many of the studies were exploratory or require further development to establish reliable, accurate measures across larger samples.

The field of physical activity measurement is rapidly developing; however, emerging analytical techniques have only achieved variable success in relatively small samples, and the degree of measurement accuracy across a range of activities has been inconsistent. It is of importance to establish the degree of accuracy achieved by using these techniques for researchers to make an informed choice on analytical approach. Further, future studies should include more detailed participant characteristics, as many individual factors affecting gait and physical activity characterisation vary by age, sex and motor competence. Despite the different techniques undertaken, these problems were consistently found. Consequently, as methods develop, it is recommended that ‘qualities’ of different activities, such as characteristics of gait, activity duration and idiosyncratic differences be further investigated in controlled, semi-controlled and free-play settings.

3.8 Summary and Conclusion

The literature review in this chapter has summarised the current evidence base surrounding physical activity and its relationship to health, recess, motor competence/FMS, body mass index and energy expenditure, whilst also appreciating the current physical activity guidelines. Further, a comprehensive and systematic review of accelerometry, classic and novel analytics and considerations in physical activity research was detailed.

Physical activity is a complex construct and should not be pigeonholed to simply quantity of activity, it may pertain to physical behaviour, movement quality, characteristics of movement, joint angles during movement, force production, motor competency, volume of activity, or even psychological constructs [122]. A substantial amount of research using accelerometers to examine physical activity has focused far more acutely on examining characteristics of movements in a contextualised setting, to later be applied to a wider application [18,19,209]. In the literature, the general reference to physical activity refers to the idea of capturing overall quantity, however, as noted physical activity is an umbrella term, for which many things could be inferred. For example, posture classification, movement classification, EE estimation, fall detection or balance and control assessment, frequency component or gait analysis [18,19]. Physical activity, measured by overall quantity is demonstrably unresponsive to interventions, as a systematic review by Metcalf, et al. [210] found that physical activity interventions only improve physical activity quantity, on average, by four minutes per day. Further, Altenburg, et al. [211] found interventions specifically designed to target sedentary behaviour are equally as ineffective. It is therefore this authors' recommendation that accelerometers placement and explicit use and application be better defined.

It is apparent, however, that physical activity is linked with several positive factors through the life course. It is also clear from the literature the deleterious impact inactivity, and factors such as excess body mass, can have on physical health, fundamental movement skill and movement quality. However, there is a dearth of literature presenting techniques capable of accurately and reliably quantifying the quality of movement across ages. Therefore, the overarching aim of this thesis is to characterise and profile children's physical activity movement and gait quality.

3.8.1 Objectives

1. To introduce a novel accelerometry-based device and investigate its suitability, accuracy and validity in a mechanically controlled setting and during controlled and semi-controlled activity (experimental chapter 1).
2. To investigate how movement quality and gait characteristics cluster during a standardised fitness test (9-11y; experimental chapter 2).
3. To investigate how movement quality and gait characteristics cluster during recess (9-11y; experimental chapter 3).
4. To investigate how movement quality and gait characteristics during free-play, and how they cluster with motor competency (3-5y; experimental chapter 4).

4.0 General methodology

This chapter describes the general methods used within this thesis. Further specific details of individual studies and review of measurement techniques are outlined in the relevant experimental chapters and appendices.

4.1 Ethical approval

Ethical approval for experimental chapters 1 (PG/2014/009), 2 (PG/2014/12), and 3 (PG/2014/37)) was granted in agreement with the guidelines and policies of the Swansea University research ethics committee (REC). Ethical approval for the study in experimental chapter 4 was approved by the NRES committee Yorkshire and the Humber (12/YH/0334). For all experimental chapters, information sheets were developed for children, parents and school staff and prior to study engagement explicit informed parental consent, school consent and child assent was attained (see appendices).

4.2 Instruments and procedures

SlamTracker

This SlamTracker is micro-electromechanical device that measures both dynamic acceleration resulting from motion or shock and static acceleration, such as gravity, that allows the device to be used as a tilt sensor. The sensor is a polysilicon surface-micro machined structure built on top of a silicon wafer. Polysilicon springs suspend the structure over the surface of the wafer and provide a resistance against forces due to applied acceleration. Deflection of the structure is measured using differential capacitors that consist of independent fixed plates and plates attached to the moving mass. Acceleration deflects the proof mass and unbalances the differential capacitor, resulting in a sensor output whose amplitude is proportional to acceleration. Phase-sensitive demodulation is used to determine the magnitude and polarity of the acceleration. This device incorporates a tri-axial accelerometer with a +/- 16g dynamic range, 3.9mg point resolution and a 13-bit resolution and a tri-axial magnetometer with a +/- 1.3 gauss range and 12-bit resolution (ADXL345 sensor, Analog Devices). It was housed in a small plastic case and, in experimental chapters 1, 2, 3, and 4, was mounted via a Velcro strap to the lateral malleolar prominence of the fibula of the dominant leg and set to record at 40 Hz (Figure 3, Figure 3, Figure 4).

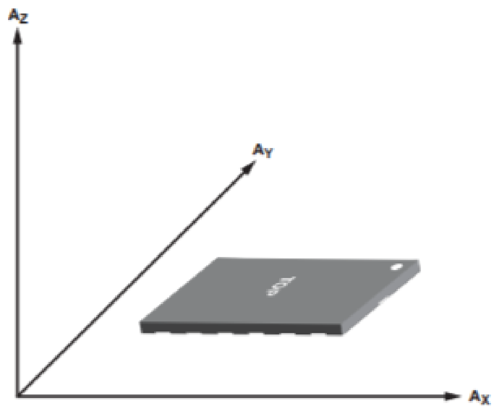

Figure 2. Axes of acceleration sensitivity

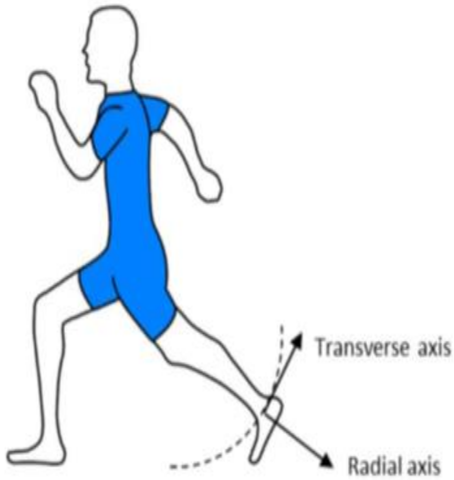

Figure 3. Diagram of accelerometer placement

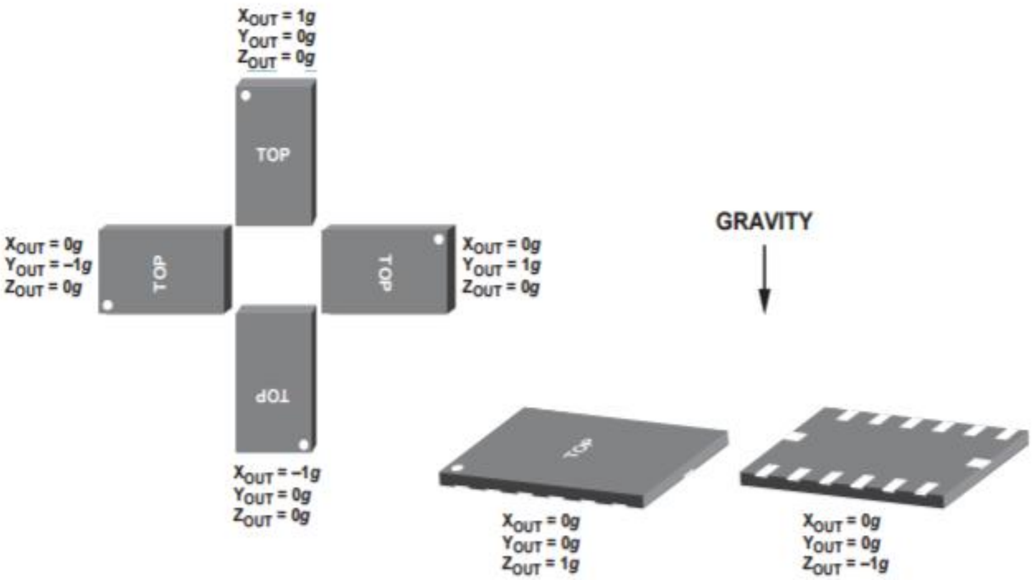

Figure 4. Output Response vs. Orientation to Gravity

Anthropometrics

Following recruitment, anthropometric measures of children's stature and body mass were recorded to allow characterisation of the sample population. Body mass was measured to the nearest 0.1 kg using Seca digital scales (SECA, Hamburg, Germany), stature to the nearest 0.1 cm using a stadiometer (SECA, Hamburg, Germany) and sitting stature to the nearest 0.1cm using a seated stadiometer (Holtain, Crymych, UK). To ensure standardisation in the measurement of anthropometric variables the standard procedures outlined by Lohmann, et al. [212] were followed.

To measure stature, participants were asked to stand barefoot with their heels touching the back of the stadiometer. The child was asked to look straight ahead with arms relaxed by their sides. The researcher then gently held the child's head in two hands so that light upwards pressure was applied under the jaw anteriorly and occiput (base of the skull) posteriorly to provide maximum extension of the spine. Care was taken not to tilt the head and to maintain the Frankfurt position of the head, whereby the inferior aspect of the orbit was parallel with upper margin of the ear canal [212]. The child was asked to breathe in and then out and to relax their shoulders without lifting their heels from the ground. The horizontal head plate was then lowered until it made contact with the highest point of the child's head and stature was recorded to the nearest 0.1 cm. Each participant was weighed in light clothing and asked to stand barefoot in the centre of the scales with arms by their sides. Weight was measured to the nearest 0.1 kg. Using the corresponding height and weight data, the children's BMIs were calculated. BMI was calculated as the body mass in kg divided by the square of the height in metres ($kg \cdot m^2$). Additionally, children were classified as either underweight (<5th percentile), normal weight (5th to 85th percentile), overweight (>85th to <95th percentile) or obese (≥ 95th percentile) [213].

4.4 Data Analysis

4.4.1 SlamTracker

For experimental chapters 1, 2, 3, and 4 raw triaxial acceleration and magnetometer data from the SlamTracker MEMS device were uploaded into MatLab (MATLAB version R2016a), where the subsequent characteristics; integrated acceleration, stride profile quotient, stride variability, stride frequency, stride angle, spectral purity, and time to volitional exhaustion, were derived. For ankle-mounted acceleration, characteristics used for analysis were derived from acceleration in the axis along the lower leg towards the origin of motion, termed the radial axis. The maximum impact force generated upon foot strike, F_{max}, corresponds to the peak positive value of acceleration (force vector pointing from foot to knee) and was calculated by subtracting the background static acceleration and multiplying by the participant's weight. The stride angle, α_{max} was obtained from the peak acceleration value in the negative direction. This point represented the maximum leg lift and when dynamic acceleration was zero, the radial acceleration was wholly determined by the vector component of the gravitational field, as determined by the angle of the accelerometer relative to the vertical axis. Therefore, determining the angle to which the subject's leg swings, the minimum point during the acceleration trace of the stride, A_{radial} was used in the following equation (Equation 1).

$$\alpha_{max} = acos(A_{radial}/g)$$

Equation 1. Maximum angle of foot lift

Where, α_{max} is the stride angle; $acos$ is the inverse of cosine; A_{radial}, is the minimum point during the acceleration trace of the stride; and g, is gravity.

The integrated acceleration was also determined, using an integration of the rectified signal and correspondent to the computation used to derive the standard ‘activity counts’ by other commercial devices, such as the ActiGraph [214].

As we were analysing accelerometer data taken from children performing motions such as walking and running, or ambulation, we decided to convert the time signal into the frequency domain. The frequency spectrum highlights important features of a child’s movement including stride-to-stride variation and overall complexity represented by the number of harmonics present in the spectrum, and can also be used to highlight the absence of repetitive motion thereby indicating inactivity or lower movement quality. In order to convert the data into the frequency domain the Fast Fourier transform was applied to the data. The Fast Fourier Transform computes the discrete Fourier transform (DFT) of a sequence.

Let x_0,…,x_(N-1) be a sequence of N complex numbers. The Fast Fourier transform computes the Discrete Fourier transform

$$X_k = \sum_{n=0}^{N-1} x_n . e^{-i2\pi kn/N} , k \in Z$$

Equation 2. Discrete Fourier Transform

Where, N = number of time samples, n = current sample under consideration (0 .. N-1), x_n = value of the signal at time n, k = current frequency under consideration (0 Hertz up to N-1 Hertz), X_k = amount of frequency k in the signal (amplitude and phase, a complex number), n/N is the percent of the time gone through, 2 * pi * k is the speed in radians·sec^{-1}, e^-ix is the backwards-moving circular path.

Several measures related to quality were also taken from the frequency domain. The stride frequency, *f* is identified as the first amplitude maxima. In order to determine the quality of a child’s movement - ‘Spectral purity’ was calculated from the cumulative distribution function (CDF) of the frequency spectrum.

The CDF plot is used to generate a value for spectral purity. The empirical CDF *F(x)* is defined as the proportion of X values less than or equal to some value *x*. In this case, it is the number of values less than or equal to some frequency in a spectrum being considered. A measure for spectral purity is therefore considered to be the frequency at which the midway point of the CDF (0.5) occurs. As a result, spectra that is 'clean', i.e. consisting of a tall narrow peak at the fundamental frequency and only low amount of noise and small harmonics will have a different value to spectra where there is lots of noise, a shorter wider peak, and higher peaks at the harmonics.

Cluster analysis

For experimental chapters 2, 3 and 4 a clustering algorithm was applied to the dataset. The derived characteristics (specific to each experimental chapter) from the raw acceleration traces were normalised so that they could be compared and input into an in-built clustering algorithm (MATLAB version R2016a). This algorithm performs multiple iterative processes in order to cluster the data along the columns of the dataset. The similarity or dissimilarity between metrics was determined by calculating the pairwise Euclidean distances between the values of the different metrics.

$$d_{2st} = (x_s - x_t)(x_s - x_t)'$$

Equation 3. Euclidean distance

Where, *d* is the Euclidean distance; x_s and x_t represent the data values being compared.

Once the distances between the characteristics (specific to each experimental chapter) for each child were derived, a linkage function was applied, to determine the proximity of the metrics to each other. These were paired into binary clusters, which were subsequently grouped into larger clusters until a hierarchical tree was formed. The resulting clustergram was displayed in terms of a heat map and dendrogram. The height of the link at which two observations on the dendrogram were joined was analysed using cophenetic distance (Equation 4), to demonstrate the similarity between two clusters [46,215,216]. The values for the dendrogram linkages were subsequently normalised. The cophenetic distance ratio for the overall clustergram was also measured to demonstrate how successfully the dendrogram preserved the pairwise distances between the original unmodeled data points (where 1 is maximum).

$$c = \frac{\sum_{i<j}(Y_{ij} - y)(Z_{ij} - z)}{\sqrt{\sum_{i<j}(Y_{ij} - y)^2 \sum_{i<j}(Z_{ij} - z)^2}}$$

Equation 4. Cophenetic distance equation

Where Y_{ij} is the distance between objects i and j in Y. Z_{ij} is the cophenetic distance between objects i and j, from Z. y and z are the average of Y and Z, respectively.

4.4.2 Statistical tests

All data were assessed for normal distribution before statistical tests were selected. Where the data were normally distributed the means and standard deviations were presented. Parametric inferential statistics were used to determine differences or explore associations (further details are provided in the respective study chapters). Where the data were found to be not normally distributed the median and upper and lower quartiles were presented. Non-parametric inferential statistics were used to determine differences and test for associations (further details are given within the respective study chapters).

Thesis map

Chapter	Study		Outcomes
1	SlamTracker Accuracy under Static and Controlled Movement Conditions	*Aim*	To quantify the mean, standard deviation and variance of the SlamTracker device at a range of speeds
		Key Findings	-
	Validity of Force and Angle Derivation Using Raw Accelerometry	*Aim*	-
		Key Findings	-
	A Kinematic Analysis of Fundamental Movement Skills	*Aim*	-
		Key Findings	-
2	Profiling Movement Quality and Gait Characteristics According to Body-Mass Index in Children (9-11y)	*Aim*	-
		Key Findings	-
3	Profiling Movement Quality and Gait Characteristics of Recess Activity in 9-11-year-old Primary School Children	*Aim*	-
		Key Findings	-
4	Profiling Movement and Gait Characteristics in Early-Years Children (3-5y)	*Aim*	-
		Key Findings	-

5.0 Experimental Chapter 1

5.1 SlamTracker Accuracy under Static and Controlled Movement Conditions

*this chapter is a published manuscript: Clark, C. C. T., Barnes, C.M., Holton, M.D., Summers, H.D., Stratton, G. (2016). SlamTracker Accuracy under Static and Controlled Movement Conditions. *Sport Science Review*, 25(5-6), 321-344.

5.2 Introduction

Accelerometry is the most commonly applied method for objective assessment of physical activity [34]. Traditional accelerometer devices predominantly store a summary measure of the raw acceleration signal, termed an "activity count" [40]. A count is a dimensionless unit aimed to be proportional to the average overall acceleration of the human body in a specified period of time, referred to as an "epoch" [117]. However, this relationship has been questioned due to the restrictive dynamic range of commercial accelerometers, the downstream signal processing and band-pass filtering [32,34]. Such processing and filtering is designed to remove components of the signal unrelated to human movements [41,217], however high frequency movement and noise information can escape the bandpass filter, which in turn adds unexplained variation in activity counts and incorrectly removes frequencies directly from human movement [32,35].

There are a plethora of methods that exist to filter and summarise a raw acceleration signal, the choice of which has profound implications on the interpretation of the final output [34,39]. However, as traditional accelerometers are limited in memory and battery capacity to store raw signal data, data processing stages are performed on the device itself, and this process is irreversible once the count has been stored in local memory. This irretrievable conversion prevents re-analysis of the raw accelerometer signal using novel analytics and data processing techniques.

Although a detailed synopsis of the signal processing protocol employed would be vital to enable replication of empirical data, most manufacturers of accelerometer devices state that pre-processed raw data is proprietary information. This lack of transparency on the calculation of "activity counts" prevents a comparison between different accelerometer brands, or even between versions of the same brand [40,41]. On the other hand "activity counts" derived from a raw accelerometer output have concordance with commercially developed devices ($r=0.93$, $P<0.05$), demonstrating the versatility of utilising the raw accelerometer signal [34].

Using a raw accelerometer signal, where all frequencies related to human movement are included in the signal, would allow novel analyses, such as; pattern recognition, feature extraction, machine learning, cluster analysis, data mining to be undertaken, aided by the fact the Nyquist-Shannon sampling theorem is not violated [34,200]. Further, given there is no hidden signal processing, researchers may maintain control and confidence in their outputs. So as raw accelerometers become more commonplace, it will be increasingly important to test their accuracy and variance during human movement, so device and human noise may be differentiated, and accuracy quantified [32,218].

The SlamTracker is a device that captures raw accelerometer signals without pre-processing the data, and has been shown to accurate and robust in a plethora of bi- and quadrupedal animal based studies [219-223]. Despite the extensive use of the SlamTracker device, it has not been assessed in a controlled manner. Therefore, the aim of this study was to quantify the mean, standard deviation and variance of the SlamTracker device at a range of speeds.

5.3 Methods

5.3.1 Instruments and procedures

Four tri-axial accelerometers of identical build, specifications and shape (ADXL345 sensor, Analog Devices) with a +/- 16g dynamic range, 3.9mg point resolution and a 13 bit resolution (see: [219-223] for detailed examples of previous use) underwent a one minute static condition test and were subsequently tested at nine movement conditions (three speeds at three radii), for one minute, on a motorised turntable (GPO Stylo, Manchester, UK), with speeds verified by digital tachometer (RS Digital Tachometer Model 445-9557, Corby, UK) (Table 2,Figure 5).

Table 2. Movement test conditions

	33.7 rpm	45.3 rpm	77.1 rpm
27 mm	0.09 $m \cdot s^{-1}$	0.13 $m \cdot s^{-1}$	0.22 $m \cdot s^{-1}$
56 mm	0.2 $m \cdot s^{-1}$	0.27 $m \cdot s^{-1}$	0.45 $m \cdot s^{-1}$
83 mm	0.29 $m \cdot s^{-1}$	0.39 $m \cdot s^{-1}$	0.67 $m \cdot s^{-1}$

*27, 56, 83 denote the possible radii in millimetres, 33.7, 45.3, 77.1 denote the possible speed in revolutions per minute.

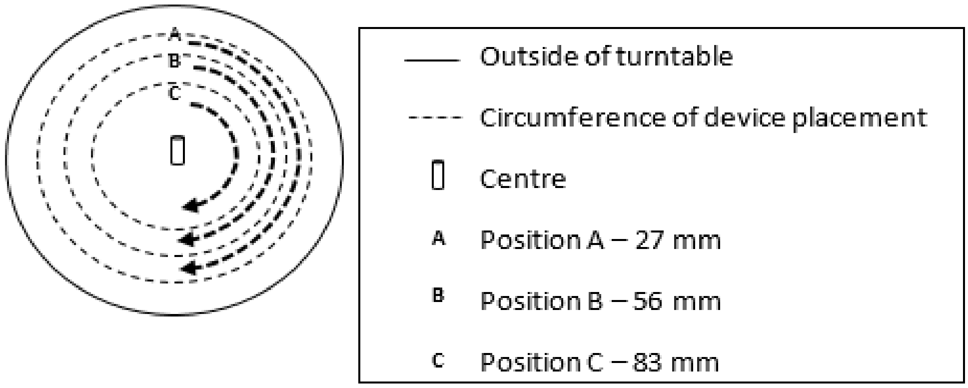

Figure 5. Turntable schematic

For the static condition, each device was tested at 20, 40, 100 and 200 Hz, and only the sensitive axis (Z) was analysed as the only force acting upon the accelerometer was gravity. All motorised turntable tests were performed at 40 Hz, with X, Y and Z axes being analysed. The decision to use 40 Hz was based on the results of the static condition test.

5.3.2 Data analysis

Raw acceleration data was uploaded into a comma separated values spreadsheet where all analyses took place. For the static condition, mean, standard deviation and coefficient of variation over the one-minute measurement epochs.

For the movement test conditions; mean, standard deviation and coefficient of variation over each one-minute test was assessed for all axes. Because axes can be subject to negative and positive *g* during movement, sample variance was calculated as the squared differences from the mean (Equation 5). For static and movement test conditions, analysis of variance (ANOVA) was assessed between all 4 devices.

Equation 5. Sample variance

$$\sigma^2 = \frac{\sum(X-\mu)^2}{N}$$

Where μ is the mean, N is the number of scores, σ^2 is the sample variance, and X is the actual numeric value.

5.4 Results

5.4.1 Static condition

The static condition test demonstrated that the Z-axis amplitude coefficient of variation improved as recording frequency reduced (Table 3). The mean Z-axis amplitude, offset to zero, across recording frequencies is shown in Figure 6. There were no significant differences between devices.

Table 3. Static condition test

Frequency	Mean	SD	CV
200	0.918	0.009	0.01
100	0.923	0.004	0.005
40	0.904	0.004	0.004
20	0.913	0.004	0.004

Mean (g), standard deviation and coefficient of variation (%) values for recording frequencies; 20, 40, 100 and 200 Hz, respectively.

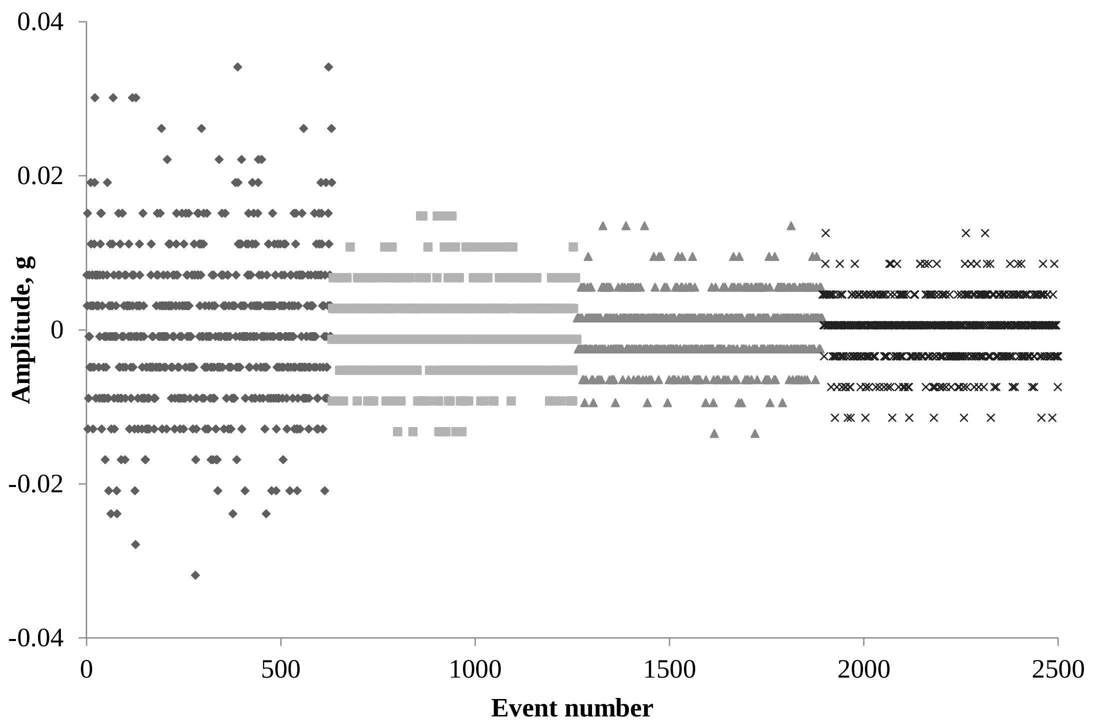

Figure 6. Amplitude for accelerometer Z-axis under no movement condition for different sampling frequencies.

Crosses denote device recordings at 20 Hz; closed triangles denote device recordings at 40 Hz, closed squares denote device recordings at100 Hz, closed diamonds denote device recordings at 200 Hz.

5.4.2 Movement conditions

The mean (SD) and sample variance for the X, Y and Z axes during all movement condition tests are detailed in Table 4 and there were no significant differences between devices.

Table 4. Movement condition tests at nine speeds.

Axis	0.09 m·s-1	0.13 m·s-1	0.2 m·s-1	0.22 m·s-1	0.27 m·s-1	0.29 m·s-1	0.39 m·s-1	0.45 m·s-1	0.67 m·s-1
X (g)	-0.046 (0.02)	-0.025 (0.01)	-0.03 (0.01)	-0.001 (0.01)	-0.021 (0.01)	-0.028 (0.02)	-0.006 (0.02)	-0.007 (0.01)	-0.048 (0.02)
	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
Y (g)	0.019 (0.01)	0.017 (0.01)	0.019 (0.01)	0.018 (0.02)	0.016 (0.01)	0.019 (0.01)	0.02 (0.03)	0.017 (0.02)	0.019 (0.01)
	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	0.001	<0.001	<0.001
Z (g)	0.855 (0.02)	0.858 (0.02)	0.856 (0.02)	0.855 (0.02)	0.857 (0.02)	0.857 (0.02)	0.856 (0.02)	0.855 (0.02)	0.853 (0.02)
	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001

Data reported as: Mean accelerometer amplitude in *g*, (standard deviation) and sample variance in *g*. values are reported for all speeds and all axes.

5.5 Discussion

The aim of this study was to quantify the accuracy of the SlamTracker accelerometer at a range of speeds. This study found that during the static condition test 40 Hz had joint lowest CV and joint lowest SD (Table 3). For the movement condition tests, the sample variance was <0.001g across all speeds and axes (Table 4).

The static condition test was performed at a range of recording frequencies suitable for assessing physical activity [34,217]. It was found that as recording frequency was decreased, the coefficient of variation concomitantly improved, as did deviation from the mean. The highest recording frequency with the lowest coefficient of variation and lowest standard deviation was found at the 40 Hz recording frequency.

The movement condition tests found that, for all axes, the sample variance was less than 0.001 g across all speeds. This indicates that, irrelevant of speed, the SlamTracker accelerometer is reliably accurate and consistent, indicating no artefacts of the device are present during movement. This is an important finding as any artefacts or anomalies recorded during human movement assessment can be attributed to researcher error (i.e. affixing problems), tampering (i.e. participant moving device) or accidental damage (i.e. participant falling on device), as opposed to device error. Slaven, et al. [224] determined the quality of accelerometer data by applying *k*-means clustering to the raw acceleration signal mean and variance across specific, consecutive time points and reported data quality as ‘good’ or ‘poor’ by how the clustering algorithm grouped the data. Data were retained in the ‘good’ cluster if they were within ~6% of the cluster mean. The present study variance from the mean was under 1% for all axes and speeds, indicating all data points would be considered ‘good’. Further, Tawk, et al. [225] reported accelerometer amplitude variance of <0.001 *g* during a static condition test, the present study, however, found similar low levels of variance in static and movement conditions.

This study comprehensively investigated the SlamTracker acceleration signal amplitude at predominantly slow speeds, ranging from static to slow ambulation. It has been suggested that in some previous studies with a mechanical calibration or validation component ([217,226]), the mechanical device used only allowed very limited acceleration amplitude in the low frequency area [227]. It was further suggested that utilising a device that can smoothly rotate at low speeds is of paramount importance when calibrating/validating accelerometers [227]. The fact this study focussed predominantly on slow speeds is therefore a strength, as finding confidence in slow speeds demonstrates that subtle movements may be accurately attributed to human ambulation and not an artefact of device noise. It may be considered a limitation that the fastest speeds of human movement were not assessed in this study, however this device was subject to a broad band pass filter, up to 12 Hz, which has been vindicated by Wundersitz, et al. [228], who identified that filters at this frequency were most suitable to process accelerations in human running tasks, and filter out non-human motion. Further, although this is the first time the SlamTracker device has been mechanically validated, prior to human use, the SlamTracker has been extensively tested in biological tracking studies of multiple mammals, birds and ocean dwelling animals of varying sizes (see; Wilson, et al. [220]).

5.6 Conclusion

This empirical investigation has quantified sample variance and deviation from mean values for the SlamTracker. This variance may be factored in to future analyses when using raw acceleration data. The SlamTracker demonstrates low variance and minimal deviation from mean values across an extensive range of slow speeds, and processes acceleration frequencies up to 12 Hz, and is therefore suitable for assessing human movement at very slow and fast speeds. Given the accuracy in static and movement tests for raw accelerometry, combined with its capability for novel analytics [32].

Thesis map

Chapter	Study		Outcomes
1	SlamTracker Accuracy under Static and Controlled Movement Conditions	*Aim*	To quantify the mean, standard deviation and variance of the SlamTracker device at a range of speeds
		Key Findings	Sample variance was <0.001g across all speeds and axes during the movement condition tests. we conclude the SlamTracker is an accurate and reliable device for measuring the raw accelerations during human movement.
	Validity of Force and Angle Derivation Using Raw Accelerometry	*Aim*	To verify the validity of using raw accelerometry to estimate force (N) and leg angle (°) during ambulation.
		Key Findings	-
	A Kinematic Analysis of Fundamental Movement Skills	*Aim*	-
		Key Findings	-
2	Profiling Movement Quality and Gait Characteristics According to Body-Mass Index in Children (9-11y)	*Aim*	-
		Key Findings	-
3	Profiling Movement Quality and Gait Characteristics of Recess Activity in 9-11-year-old Primary School Children	*Aim*	-
		Key Findings	-
4	Profiling Movement and Gait Characteristics in Early-Years Children (3-5y)	*Aim*	-
		Key Findings	-

5.7 Validity of Force and Angle Derivation Using Raw Accelerometry

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5.8 Introduction

Accelerometers are considered to be the *de facto* standard device for objective physical activity monitoring [33,34]. The most widely used accelerometers in physical activity research (e.g. ActiGraph) use a piezoelectric lever to detect acceleration ranging from 0.05 to 2.13G. In traditional physical activity analyses, participants typically, although not exclusively, wear the accelerometer on the right hip (near to the centre of mass). Any full body movement results in displacement of the accelerometer causing the piezoelectric lever to bend. Resultantly, a signal is generated in proportion to the amount of acceleration, which subsequently generates intensity of movement output and the signal is sampled at a user specified value otherwise known as an 'epoch' [34,131,229]. Physical activity is then traditionally reported as overall quantity of activity or time spent in varying intensities [34,131,229].

Signal processing of accelerometer data has, however, progressed beyond the descriptive approach of simply quantifying overall activity using time spent in thresholds or counts per minute. Chen, et al. [117] and Yang, et al. [114] extensively reviewed the area and concluded that there are more substantive insights that will take the accelerometer data past the descriptive domain, allowing quality and movement characteristics to be accurately reported. Utilising raw accelerometer signals assessing movement characteristics such as; joint angles, force production, ambulation control and spectral components is possible. Further, future research will necessitate examining raw acceleration signals for more in-depth analyses of physical activity [114,117,190].

Physical activity is a complex construct and not simply quantity of activity, and may pertain to physical behaviour, movement quality, characteristics of movement, joint angles during movement, force production, motor competency, volume of activity, or even psychological constructs [122]. The most common definition in the literature of physical activity is, "any bodily movement produced by skeletal muscles that requires energy expenditure" [160]. However, physical activity as defined in this way does not cover all aspects of behaviour and movement that can be relevant (e.g., body postures, angles, forces, movement characteristics etc.). It has been suggested by Bussmann, et al. [122] that a clear ontology and definition is required as to what the actual outcome and criterion measures are intended to be. Taking this in to consideration, and the capability of raw accelerometry, the aim of this study was to verify the validity of using raw accelerometry to estimate force (N) and leg angle (°) during ambulation.

5.9 Methods

5.9.1 Participants and settings

A single participant was used for this case study (25y, 1.75m, 73kg, leg length: 0.8m). Approval was granted from Swansea University's Research Ethics Committee (REC), and the participant provided signed, informed consent before participation.

5.9.2 Instruments and Procedures

The participant attended the laboratory on two separate occasions. During the first occasion standing stature, leg length (measured to the nearest 0.01m) and body mass (to the nearest 0.1kg) were measured using a stadiometer (SECA, Hamburg, Germany) and digital scales (SECA, Hamburg, Germany), respectively, using standard procedures. The participant then performed eight movement tasks (four walking and four running, at volitional speed) on an embedded force platform (Kistler, model number 9286AA). The force platform was calibrated by applying known loads to the plate before and after each movement task and sampling its output, and was set to record at 1000 Hz and output force in Newtons.

On the second visit, the participant performed five runs of one-minute duration, with speed increasing in 1.5 $km{\cdot}h^{-1}$ increments from 7.0 to 13 $km{\cdot}h^{-1}$ on a motorised treadmill (Woodway, Cardiokinetics, Salford, UK). Each run was recorded using a high-resolution (350 fps) video camera (Bonita 480m, Biometrics, France) positioned medio-laterally to the participant. During the force platform and treadmill measurements the participant also wore a custom-built motion tracking and recording device, which incorporated a tri-axial accelerometer with a +/- 16g dynamic range, 3.9mg point resolution and a 13 bit resolution (with an amplitude coefficient of variation of 0.004% at 40Hz (see: [230])) (ADXL345 sensor, Analog Devices). It was housed in a small plastic case and affixed via a Velcro strap to the lateral malleolar prominence of the fibula of the right leg, where a co-ordinate system referenced to the lower leg was used (motion space rather than absolute space), in which acceleration in the axis along the lower leg towards the origin of motion (knee or hip), A_{radial} is used for all measurements - termed the radial axis. The device was set to record at 40 Hz and data were recorded onto a microSD card.

5.9.3 Data analysis

Data analysis was carried out using custom algorithms written in the MATLAB software environment (MATLAB version R2016a). Low and high frequency device noise was removed by passing the raw data through a broad band-pass filter (0.5Hz to 12 Hz) i.e. only frequencies within the normal range of walking and running frequencies were accepted.

For the tri-axial accelerometer, the maximum impact force generated upon foot strike, F_{max}, corresponds to the peak positive value of acceleration (Figure 1) and was calculated by subtracting the background static acceleration ($1g$) and multiplying by the participant's body mass. F_{max} was validated against the value derived by the force platform using Pearson's product-moment correlation coefficient analysis.

For the tri-axial accelerometer, the maximum angle of foot lift, α_{max} was obtained from the peak acceleration value in the negative direction (Figure 8). At this point of maximum leg lift the dynamic acceleration is zero and the radial acceleration is wholly determined by the vector component of the gravitational field, as determined by the angle of the accelerometer relative to the vertical axis. Therefore, to determine the angle to which the participant's leg swings the minimum point during the acceleration trace of the stride, A_{radial} is used in the following equation:

Equation 6. Maximum foot lift angle

$$\alpha_{max} = acos(A_{radial}/g)$$

Where, α_{max} is the stride angle; $acos$ is the inverse of cosine; A_{radial}, is the minimum point during the acceleration trace of the stride; and g, is gravity.

Recorded video data was uploaded into MatLab, where manual measurement of the leg position from the image frames was used to determine maximum angle of the foot lift using the knee as the reference point. Following this, validation of the accelerometer derived angle against the video derived angle was performed using Pearson's product-moment correlation coefficient analysis.

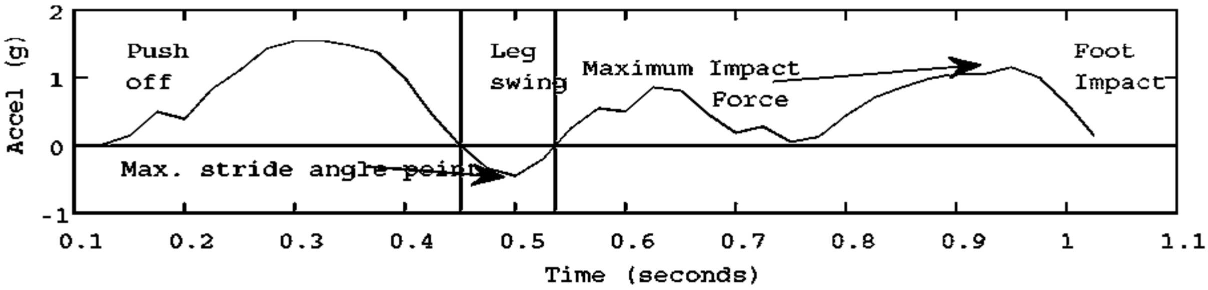

Figure 7. Radial acceleration for one stride

5.10 Results

Accelerometer derived angle was significantly correlated with video derived angle (r=0.98) (Figure 8), and were within 8±2.4% of video values. Accelerometer derived force was significantly correlated with force platform derived force (r=0.98) (Figure 9), and were within 0.67±6% of force platform values.

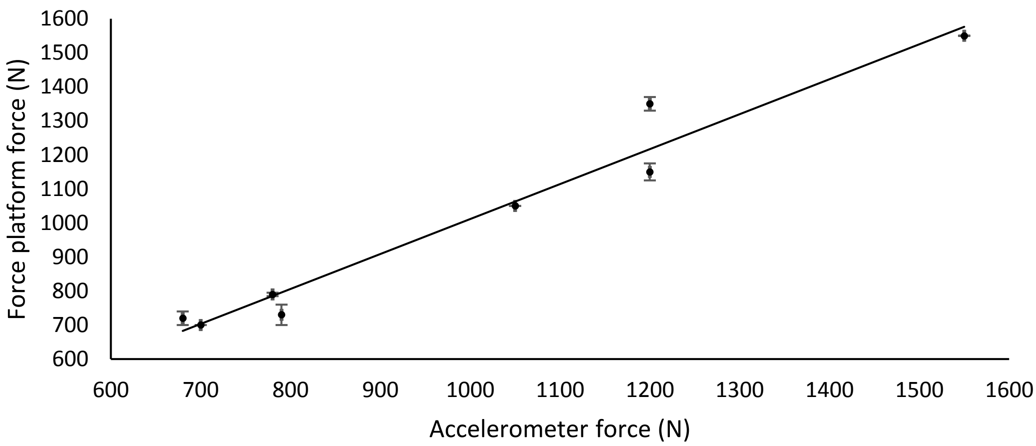

Figure 8. Video vs. accelerometer derived angle (°).

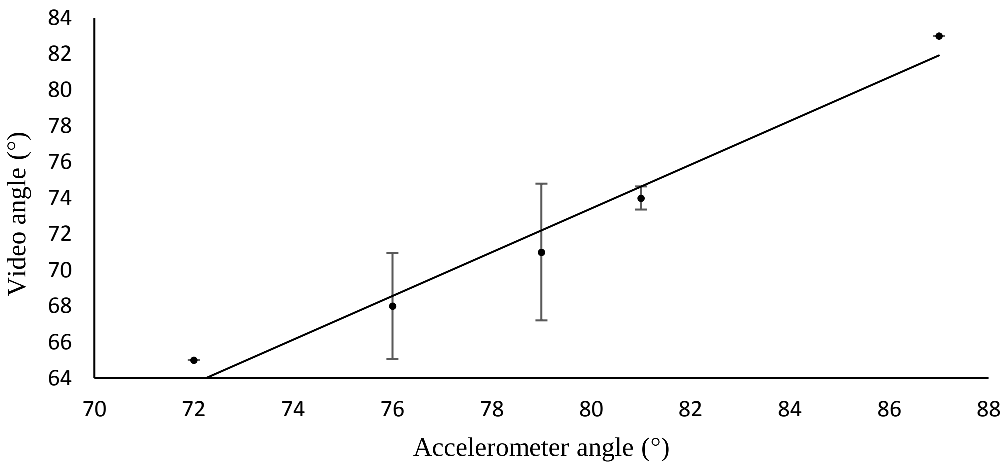

Figure 9. Force platform vs. accelerometer derived force (N).

5.11 Discussion

The aim of this study was to verify the validity of using raw accelerometry to estimate force (N) and leg angle (°) during ambulation. In accord with the aim of this study, the key finding was that a tri-axial accelerometer raw signal is significantly related to criterion measures for angle estimation and force derivation. The method for estimating angle (°) using an accelerometer significantly correlated with video verified angle estimation (r=0.98, *P*=0.001). The method for deriving force (N) using an accelerometer significantly correlated with force platform verified values (r=0.98, *P*=0.001).

5.11.1 Angle estimation

Accelerometers can equate with kinematics, goniometers and cameras for angle estimation. Djuric-Jovicic, et al. [231] demonstrated accelerometry estimated ankle angle correlated to a criterion measure strongly (r=0.85), although, the present study found a stronger correlation coefficient (r=0.98), indicating strength in this method of estimation. The result found in this study, Williamson, et al. [232], and Djuric-Jovicic, et al. [231] indicated a small, mean over or under estimation of angle when derived through accelerometer signal processing, however all angle estimations were within 8% of criterion measured values for all three studies. The present study sought to identify one particular characteristic of the walking/running, angle maxima, which explains the high level of agreement. Whilst Djuric-Jovicic, et al. [231] reported lower correlation coefficients using a criterion measure, they used a continuous angle measurement indicating that accelerometers are extremely robust and capable of continuous and discrete measurements of angle.

5.11.2 Force estimation

The utility of accelerometers is widely recognised, and with the proliferation of novel technologies and signal processing techniques [34], there use is expanding. In addition to being able to accurately estimate angles, the ability to estimate force production using accelerometers is also possible. This study has shown accelerometry can be used to very accurately and reliably estimate force production during ambulation at varying speeds (r=0.98) to within <1% of force platform recorded values. This has also been demonstrated for counter-movement jumping, Howard, et al. [233], found both minimum eccentric force and maximum concentric force were accurately estimated, in comparison to force platforms although there were higher intra-class correlations in the minimum eccentric force (r=0.93), compared to maximum concentric force (r=0.6). Further, ground reaction force estimation has yielded promising results.

Simons, et al. [234] found correlation coefficients of up to r=0.86, whilst Pouliot-Laforte, et al. [235] reported a correlation coefficient of r=0.96, and noted 95% limits of agreement between 17% and 31%. This indicates that the force derivation in this study yielded higher accuracy and correlation coefficient to a criterion measure than other comparable studies. One potential reason for the higher accuracy in this study is that the accelerometer was ankle mounted, opposed to hip mounted. Studies using hip mounted accelerometers acknowledged that forces were routinely underestimated, this could in part be due to low band-pass filters applied to the accelerometers. Wundersitz, et al. [228] identified that filters with at least an 8 or 10 Hz cut-off frequency were most suitable to process accelerations in walking and running tasks. An alternative explanation is poor choice in device placement, where the errors found may be due to the distance between the accelerometer worn on the trunk and the criterion measure chosen, such as a force plate located on the ground [228]. Although centre of mass locale are widely accepted for their correlation with energy expenditure [236]. Moreover if identifying a force inherent to a specific movement (i.e. running or jumping) opposed to energy expenditure is the aim, then the ankle (in the case of running or jumping) may be more appropriate [237].

5.11.3 Conclusion

Novel signal processing techniques have enabled researchers to use raw tri-axial accelerometry to accurately and reliably estimate movement characteristics such as force and joint angles. Congruent with this statement, it was concluded that the SlamTracker raw accelerometer can be accurately and reliably used to estimate force production and angle estimation against criterion measures.

Thesis map

Chapter	Study		Outcomes
1	SlamTracker Accuracy under Static and Controlled Movement Conditions	*Aim*	To quantify the mean, standard deviation and variance of the SlamTracker device at a range of speeds
		Key Findings	Sample variance was <0.001g across all speeds and axes during the movement condition tests. In conclusion, the SlamTracker is shown to be an accurate and reliable device for measuring the raw accelerations of movement.
	Validity of Force and Angle Derivation Using Raw Accelerometry	*Aim*	To verify the validity of using raw accelerometry to estimate force (N) and leg angle (°) during ambulation.
		Key Findings	Angle estimation (°) and force derivation (N), using an accelerometer, significantly correlated with video verified angle estimation (r=0.98, p=0.001) and force platform verified values (r=0.98, p=0.001), respectively.
	A Kinematic Analysis of Fundamental Movement Skills	*Aim*	To characterise the relationship between facets of fundamental movement and, to characterise the relationship between overall integrated acceleration and three-dimensional kinematic variables whilst performing fundamental movement skills.
		Key Findings	-
2	Profiling Movement Quality and Gait Characteristics According to Body-Mass Index in Children (9-11y)	*Aim*	-
		Key Findings	-
3	Profiling Movement Quality and Gait Characteristics of Recess Activity in 9-11-year-old Primary School Children	*Aim*	-
		Key Findings	-
4	Profiling Movement and Gait Characteristics in Early-Years Children (3-5y)	*Aim*	-
		Key Findings	-

5.12 A Kinematic Analysis of Fundamental Movement Skills

*this chapter is a published manuscript: Clark, C. C. T., Barnes, C. M., Holton, M. D., Summers, H. D., Stratton, G. (2016). A Kinematic Analysis of Fundamental Movement Skills. *Sport Science Review, 3-4*, 261-275.

5.13 Introduction

Participation in physical activity is vital for enhancing children's physical, social, cognitive and psychological development [76]. Higher levels of physical activity in children are associated with improved fitness (both cardio-respiratory fitness and muscular strength) [75], enhanced bone health and reduced body fat [76]. Further, children who frequently participate in physical activity demonstrate reduced symptoms of anxiety and depression, and improved self-esteem and confidence [76].

Accelerometers are the *de facto* standard in objectively measuring physical activity [33,34]. Commercial devices (such as; ActiGraph, ActiCal) measure activity in the form of 'activity counts', which summarize data over a user-specified epoch, reducing the burden of data management, analysis, and interpretation [35]. However, information about the raw accelerometer signal is irretrievably lost and a full picture of physical activity and fundamental movement quality and competency is overlooked.

Fundamental movement skills are considered the basic building blocks for movement and provide the foundation for specialized and sport-specific movement skills required for participation in a variety of physical activities. Fundamental movements skills can be categorized as locomotor (e.g., run, hop, jump, leap), object-control (e.g., throw, catch, kick, strike), and stability (e.g., static balance) skills [86]. There is strong evidence to suggest a positive association between fundamental movement skill competency and physical activity in children [92]. Although some studies have relied upon self-report measures of physical activity [238,239], a recent review by Barnett, et al. [24] contended the positive relationship between functional movement skills and health related benefits, and highlighted the findings of Holfelder, et al. [94] and Lubans, et al. [92] who reported predominantly positive associations in their respective systematic reviews. Further, it has been reported, by Cohen, et al. [240], that overall daily physical activity is positively correlated with locomotor and object control competency.

Robust kinematics have been used to successfully analyse multi-dimensional facets of human movement [241], and in relation to fundamental movement skills, can offer in depth analysis across; object control i.e. throwing velocity and release angle [242], stability i.e. centre of mass movement [243] and locomotion i.e. stride angle [244]. A kinematic analysis of fundamental movement skills has not been performed prior to this study, but would provide a vital piece of evidence for future research, elucidating the range in fundamental movement skills in a homogenous population, and providing an initial research base to build upon. Therefore, the aims of this study were to, (1) characterise the relationship between facets of fundamental movement and, (2) characterise the relationship between overall integrated acceleration and three-dimensional kinematic variables whilst performing fundamental movement skills.

5.14 Methods

5.14.1 Participants and settings

A sample of 11 (four female) participants (10±0.8y, 1.41±0.07m, 33.4±8.6kg, body mass index; 16.4±3.1 $kg{\cdot}m^2$) were recruited to take part in this study. The participants were invited to attend the Swansea University Biomechanics and Motion laboratory on one occasion, had anthropometric variables recorded and performed a series of fundamental movement tasks. This research was conducted in agreement with the guidelines and policies of the institutional ethics committee.

5.14.2 Instruments and procedures

After familiarisation with the laboratory surroundings, tasks and five-minute warm-up, children performed a series of stepwise tasks (Table 5), whilst a three-dimensional motion capture system (Vicon, MX13) recorded all movements. Participants also wore custom built Micro Electro-Mechanical System (MEMS) based devices, which incorporated a tri-axial accelerometer with a +/- 16g dynamic range, 3.9mg point resolution and a 13-bit resolution (with a z-axis amplitude coefficient of variation of 0.004 at 40hz) (ADXL345 sensor, Analog Devices). It was housed in a small plastic case and affixed via a Velcro strap to; (1) the lateral malleolar prominence of the fibula of the dominant leg, (2) between the radial and ulnar styloid processes of the dominant hand and (3) mounted to the right side of the hip of each individual and set to record at 40 Hz.

Table 5. Fundamental movement tasks

	Task	Description
1	Overarm throw	Using the dominant hand, throwing a standard tennis ball at a target, five meters away, using an overarm throw.
2	Balance task	Walking along an up-turned bench, whilst maintaining balance and control.
3	Walk	Walk at self-selected speed along five metres.
4	Jog	Jog at self-selected speed along five metres.
5	Sprint	Run at maximal speed along five metres.

*1= throw, 2= balance, 3-5= locomotion

Anthropometrics

Standing and seated stature (measured to the nearest 0.01m) and body mass (to the nearest 0.1kg) were measured using a stadiometer (SECA, Hamburg, Germany), sitting stadiometer (Holtain, Crymych, UK) and digital scales (SECA, Hamburg, Germany), respectively, using standard procedures [212].

Motion capture

Motion capture was performed using the Vicon MX13 motion capture system (Vicon Peak, Oxford, UK), including twelve cameras sampling at 200 frames per second. For kinematic analysis, 39 retro-reflective markers of 14 mm diameter were attached to specific anatomical landmarks (Plug-In Gait Marker Set, Vicon Peak, Oxford, UK) (see methodology section) of every participant. Three-dimensional coordinates of the 39 markers were reconstructed with the Nexus software (Nexus 2.0, Vicon, Oxford, UK) and smoothed using cross validation splines [245]. Both static and dynamic calibrations were performed, and residuals of less than 2 mm from each camera were deemed acceptable.

The 39 retro-reflective marker were placed at the following anatomical locations; the right forehead (RFHD), left forehead (LFHD), right back of head (RBHD), left back of head (LBHD), the 7th cervical vertebrae (C7), the 10th thoracic vertebrae (T10), the clavicle (CLAV), sternum (STRN), the right scapula (RBAK), the left shoulder at the acromio-clavicular joint (LSHO), the right shoulder at the acromio-clavicular joint (RSHO), the left upper arm between shoulder and elbow (LUPA), the right upper arm between shoulder and elbow (RUPA), the lateral epicondyle of the left elbow (LELB), the lateral epicondyle of the right elbow (RELB), the left forearm between the elbow and wrist (LFRA), the right forearm between the elbow and wrist (RFRA), the medial and lateral left wrist (LWRA and LWRB, respectively), the medial and lateral right wrist (RWRA and RWRB, respectively), the left hand second metacarpal head (LFIN), the right hand second metacarpal head (RFIN), the left anterior superior iliac spine (LASI), the right anterior superior iliac spine (RASI), the left posterior superior iliac spine (LPSI), the right posterior superior iliac spine (RPSI), the lateral epicondyle of the left knee (LKNE), the lateral epicondyle and the right knee (RKNE), the left thigh between the lateral epicondyle of the knee and greater trochanter (LTHI), the right thigh between the lateral epicondyle of the knee and greater trochanter (RTHI), the left lateral malleolus (LANK), the right lateral malleolus (RANK), the left tibia between the lateral epicondyle of the knee and lateral malleolus (LTIB), the right tibia between the lateral epicondyle of the knee and lateral malleolus (RTIB), the left foot second metatarsal head (LTOE), the right foot second metatarsal head (RTOE), the left heel placed on the calcaneous at the same height as the left foot second metatarsal head (LHEE), the right heel placed on the calcaneous at the same height as the right foot second metatarsal head (RHEE). Which has been used previously with a child population [246,247].

5.14.3 Data analysis

MEMS

Raw acceleration data was uploaded into MatLab (MATLAB version R2016a), where the subsequent movement characteristic; integrated acceleration was derived. The integrated acceleration was determined using an integration of the rectified raw acceleration signal in the radial axis and correspondent to the computation used to derive the standard ‘activity counts’ by other commercial devices [214].

Vicon

All corresponding data and video files were first uploaded into Vicon Nexus software and underwent in-depth analysis. Firstly, a reconstruct and labelling process was performed, allowing conversion of stereoscopic images into a three-dimensional movement. Once a three-dimensional movement had been established, a functional skeleton calibration was performed and all body segments, joint centres, bone lengths and marker movements were comprehensively modelled and trajectories were manually filtered using Woltring cross validation splines. Every single frame was scrutinised for fluidity and accuracy and marker quality was assessed. Using the three-dimensional reconstruction, maximum elbow flexion (°), maximum shoulder external rotation (°), and maximum internal shoulder rotation velocity ($°\cdot s^{-1}$) were computed for the overarm throw, mediolateral centre of mass range (cm) and coefficient of variation (%) were computed for the balance task and maximum stride angle (defined as maximum hip extension) was computed for the walk, jog and sprint. Further coefficient of variation between participants for each characteristic was computed. Following this, all kinematic and raw acceleration data was converted into a comma separated values spread sheet for; descriptive statistical analysis, Pearson's product-moment correlation coefficient analysis, and assessed for statistical significance.

5.15 Results

The results of this study found that there were a number of significant relationships within specific movement tasks (throwing, locomotion and balance) and across movement tasks. Descriptive statistics are detailed in Table 6. All participants were found to have completed correspondent overall activity for the fundamental movement tasks (Hip: 34±3 counts, Ankle: 50±5 counts, CV: 10%).

5.15.1 Facets of Fundamental Movement

For overarm throwing, there was a significant correlation between maximum shoulder external rotation (°) and maximum shoulder internal rotation velocity ($°\cdot s^{-1}$) ($r=0.86$, $P<0.001$). For the balance task, there was a significant positive correlation coefficient between mediolateral centre of mass range (cm) and centre of mass coefficient of variation (%) ($r=0.83$, $P<0.001$). For the locomotion tasks, there was a significant strong positive correlation found between maximum stride angle (°) in the jog and walk ($r=0.74$, $P=0.01$). Finally, there was a significant correlation found between maximum sprint stride angle and maximum shoulder internal rotation velocity ($°\cdot s^{-1}$) ($r=0.67$, $P<0.02$).

Table 6. Mean ± SD of fundamental movement variables

	THROW			BALANCE		LOCOMOTION		
	Max ER (°)	Max EF (°)	Max IR velocity (°·s^{-1})	CoM range (cm)	CoM CoV (%)	Max sprint SA (°)	Max jog SA (°)	Max walk SA (°)
Mean	117.93	111.42	4021.34	42.26	0.08	27.15	19.97	14.18
SD	43.48	12.14	1667.19	12.25	0.05	3.62	3.30	2.86
CV (%)	37	11	41	21	65	13	17	20

*Max ER: maximum shoulder external rotation, Max EF: maximum elbow flexion, Max IR velocity: maximum shoulder internal rotation velocity, CoM range: mediolateral centre of mass range, CoM CoV: centre of mass coefficient of variation, Max sprint SA: maximum sprint stride angle, Max jog SA: maximum jog stride angle, Max walk SA: maximum walk stride angle. CV: coefficient of variation, SD: standard deviation.

5.15.2 Integrated Acceleration vs. Kinematic Variables

Hip and ankle derived integrated acceleration were positively correlated (r=0.97, *p*<0.001). For locomotion, integrated acceleration at the hip (r=0.96, *p*<0.001) and ankle (r=0.97, *p*<0.001) was significantly correlated with maximum sprint stride angle. For overarm throwing, there was a strong positive correlation between maximum internal rotation velocity and integrated acceleration at the ankle (r=0.6, *p*=0.05).

5.16 Discussion

The aims of this study were to, (1) characterise the relationship between facets of fundamental movement and, (2) characterise the relationship between overall integrated acceleration and three-dimensional kinematic variables whilst performing fundamental movement skills. This study identified a number of relationships between and within facets of fundamental movement; maximum shoulder external rotation (°) and maximum shoulder internal rotation velocity (°·s^{-1}) (r=0.86, *P*<0.001), mediolateral centre of mass range (cm) and centre of mass coefficient of variation (%) (r=0.83, *P*<0.001), maximum stride angle (°) in the jog and walk (r=0.74, *P*=0.01) and maximum sprint stride angle and maximum shoulder internal rotation velocity (°·s^{-1}) (r=0.67, *P*=0.02) were significantly correlated. This study also identified relationships between maximum sprint stride angle (hip: r=0.96, *P*<0.001, ankle: r=0.97, *P*<0.001) and maximum internal rotation velocity (ankle: r=0.6, *P*=0.05) to overall integrated acceleration.

5.16.1 Facets of Fundamental Movement

Task specific variables, i.e. overarm throw, balance and locomotion were found to be significantly correlated. The movement required to powerfully throw a ball, overarm, follows a specific developmental sequence [248], where there is a wind-up, stride, arm-cocking, arm acceleration, arm deceleration and follow-through [249]. In this sequence of movement, the external and internal rotation of the shoulder is described as one of the most dynamic movements in the human body [249] and is pivotal in power production in overarm throwing. It is therefore necessary for a greater external rotation to produce greater internal rotation velocity.

For stability tasks, it is common to assess this fundamental movement skill using balance beams etc. as a proxy for stability and control [92]. In order to competently perform a stability task, it necessitates controlled movement, resulting in minimal mediolateral range, i.e. wobble, and by reducing wobble, centre of mass variation would concomitantly be reduced.

For locomotion tasks, only the jog and walk stride angle were correlated, indicating that an individual's normal gait has minimal bearing on maximum effort gait. The increase in stride angle from volitional walking and jogging was only ~5°, meaning that the increase in speed from walk to jog was only minimal. However, the difference in stride angle for the sprint was markedly increased (walk-sprint: 13°).

The only significant cross fundamental movement skill relationship was between maximum sprint stride angle and maximum internal rotation velocity. Although these tasks represent very different mechanics and movements, they are both very strongly related to power production. The maximum speed sprint relies upon explosive leg power [250] and an overarm throw relies upon power generated, predominantly, from the shoulder and trunk [251]. Indicating that if a child is competent and powerful in one fundamental movement skill, it will transfer across skills. It has been shown previously that children who demonstrate competence in locomotion are also competent during object-control tasks [92,240]. Despite the relationship found, only 45% of the variance would be explained. However given the nature of developmental sequence involved in overarm throwing, there are a number of trunk, arm and shoulder components that are not present nor required in locomotion, and the step portion of a throw is only a small part of the throwing sequence, meaning a large proportion of movement during internal rotation of the shoulder would be restricted to the upper body [252,253].

5.16.2 Integrated acceleration vs. Fundamental Movement

Locomotion was found to have the greatest correlation to hip and ankle integrated acceleration, this finding can be explained given that the method for calculating integrated activity requires using the radial axis (i.e. along the lower leg towards the origin of motion). Therefore, greater movement along that axis, should result in greater integrated acceleration.

The only other facet of fundamental movement that correlated with integrated acceleration was internal rotation velocity of the overarm throw, however at the ankle only. Given the mechanics of a powerful overarm throw and the developmental sequence of step and trunk action during overarm throwing, there is a strong step action component [252,253], where there is a contralateral step forward, and the ipsilateral foot is stretched backwards over half the child's standing stature [248]. This large and powerful ipsilateral to contralateral foot range would explain the moderate relationship to integrated acceleration. Nevertheless, only 36% of the variance was accounted for between these two characteristics.

However, similar to the relationship between maximum sprint angle and internal rotation velocity above, given the action sequence involved for an overarm throw, there are a substantial components that are not present in locomotion, and the ipsilateral step back and contralateral step forward are only minor components of the throw, meaning a large proportion of movement during the throw would be restricted to the upper body, in particular glenohumeral, scapulothoracic, and trunk hyperextension [249,252,253].

No other facet of fundamental movement (locomotion, stability, object control) was significantly correlated to integrated acceleration, this is consistent with previously reported literature, where the relationship between object control competency and short activity bouts has been reported to be very weak; r=0.11) [240].

Finally, the overall integrated acceleration was comparable between participants (Hip: 34±3 counts, Ankle: 50±5 counts), and had a coefficient of variation of 10%, whereas characteristics derived from the three-dimensional kinematic analyses varied by up to 65%. Indicating that although overall activity may be the comparable, the characteristics of a child's movement may be noticeably different, even when completing the same activities.

5.16.3 Limitations

Although the overarm throw was assessed, the exact contribution to total external rotation by each of the shoulder components of glenohumeral, scapulothoracic, and trunk hyperextension was not quantified in this study as it went beyond the scope of the study.

This study utilised a homogenous sample of normal weight, active children, and although their overall integrated acceleration was found to be similar, the facets of fundamental movement were clearly varied, indicating that an overall measure of activity isn't sensitive enough to identify differences in competence or quality of movement.

Fundamental movement skills have previously been linked with health outcomes and physical activity, however, the links have been somewhat tenuous or weak [92,240]. It is recommended that more in depth research to dichotomise quality and quantity of activities is needed, which may be achieved through analysing raw acceleration signal features more acutely to reveal information about movement quality and competence across different BMI groups

5.16.4 Conclusion

This study identified that in a homogenous group of children performing the same fundamental movement tasks, overall integrated acceleration is consistent, whereas quality and competence variables are distinctly varied. This study also demonstrated that characteristics of specific fundamental movements are significantly correlated, as well as between certain movements, which has previously not been done using three-dimensional kinematics.

Although useful, quantity of activity is an insensitive measure, lacking the ability to identify acute changes, such as; skill acquisition, movement competency, movement quality, motor skill development and developmental disorders. For example, a comprehensive systematic review by Metcalf, et al. [210], involving circa 14,000 participants found physical activity interventions only improve physical activity duration, on average, by 4 minutes per day. The criterion measure of success of an intervention was based on the quantity of accelerometer counts, however the effect on competency or quality of locomotion or other movements, which is of fundamental importance, was overlooked. In this study, the overall activity of participants was comparable, whereas characteristics of their movement were varied (up to 65%).

Indicating that more attention should be given to fundamental differences in movement, as well overall quantity.

Using the raw acceleration signal, activity counts can be computed in an analogous fashion to commercial devices [34], however there is a clear area for growth in developing beyond simple overall activity quantification, potentially using time-series analysis of raw acceleration to highlight the fundamental differences in similar movements.

5.17 Summary: Experimental Chapter One

The overarching aims of this experimental chapter were to introduce the SlamTracker device and demonstrate its suitability, accuracy and validity across mechanical, controlled and semi-controlled activity.

Accordingly, the empirical investigation into the sample variance and deviation at a range of speeds concluded that the device reports was accurate and reliable. At all speeds a variance of less than 0.001 g was found in all axes of movement. Following this, the SlamTracker raw signal was examined, and compared to a criterion measure for joint angle estimation and force production during locomotion. We confirmed that the raw signal of the SlamTracker accelerometer allowed accurate estimation of joint angle maxima ($r=0.98$, $P=0.001$) and maximal force production ($r=0.98$, $P=0.001$) at a range of ambulatory speeds. The final section of this experimental chapter sought to demonstrate the utility of the SlamTracker by identifying overall activity (integrated acceleration), in comparison to three-dimensional kinematic variables, such as; sprint angle maxima, internal rotation velocity during an overarm throw, mediolateral centre of mass range. It was found that overall quantity of activity was comparable across participants, with a coefficient of variation of 10%, whilst for the three-dimensional kinematic variables there were coefficient of variations up to 65%.

Overall, these studies were able to confirm the accuracy, suitability and validity of the SlamTracker. In addition, it was demonstrated that complex movement characteristics i.e. joint angle, force production and overall quantity of activity, can be accurately computed. Further, in children completing the same activity, there are fundamental differences in the way each child performs the activity. The subsequent conclusion was that the processing of the raw accelerometry data and application of novel analytics allowed children's fundamental movement qualities to be examined.

The subsequent experimental chapters of this thesis will aim to analyse and characterise movement quality characteristics in children during (i) semi-controlled field measure of cardiorespiratory fitness, and (ii) during un-controlled activity, i.e. recess or free-play.

Thesis map

Chapter	Study		Outcomes
1	SlamTracker Accuracy under Static and Controlled Movement Conditions	*Aim*	To quantify the mean, standard deviation and variance of the SlamTracker device at a range of speeds
		Key Findings	Sample variance was <0.001g across all speeds and axes during the movement condition tests. In conclusion, the SlamTracker is shown to be an accurate and reliable device for measuring the raw accelerations of movement.
	Validity of Force and Angle Derivation Using Raw Accelerometry	*Aim*	To verify the validity of using raw accelerometry to estimate force (N) and leg angle (°) during ambulation.
		Key Findings	Angle estimation (°) and force derivation (N), using an accelerometer, significantly correlated with video verified angle estimation (r=0.98, p=0.001) and force platform verified values (r=0.98, p=0.001), respectively.
	A Kinematic Analysis of Fundamental Movement Skills	*Aim*	To characterise the relationship between facets of fundamental movement and, to characterise the relationship between overall integrated acceleration and three-dimensional kinematic variables whilst performing fundamental movement skills.
		Key Findings	Overall integrated acceleration was comparable between participants (CV: 10.5), whereas three-dimensional variables varied by up to 65%. Indicating that although overall activity may be correspondent, the characteristics of a child's movement may be highly varied.
2	Profiling Movement Quality and Gait Characteristics According to Body-Mass Index in Children (9-11y)	*Aim*	To apply automated, novel analyses to characterise the movement quality of children during the multi-stage fitness test, and to report how movement quality characteristics of gait cluster according to BMI
		Key Findings	-
3	Profiling Movement Quality and Gait Characteristics of Recess Activity in 9-11-year-old Primary School Children	*Aim*	-
		Key Findings	-
4	Profiling Movement and Gait Characteristics in Early-Years Children (3-5y)	*Aim*	-
		Key Findings	-

6.0 Experimental Chapter 2

6.1 Profiling Movement Quality and Gait Characteristics According to Body-Mass Index in Children (9-11y)

*this chapter is a published manuscript: Clark, C. C. T., Barnes, C. M., Holton, M. D., Summers, H. D., Stratton, G. (2016). Profiling movement quality and gait characteristics according to body-mass index in children (9–11 y). *Human Movement Science, 49*, 291-300.

6.2 Introduction

Physical inactivity is one of the most widespread non-communicable diseases worldwide [2], and despite recognition of the importance of physical activity, the use of the appropriate measurement and analytical techniques is currently limited, especially with regard to gait and movement quality characteristics that make up physical activity. Accelerometers are the *de facto* standard in objectively measuring physical activity [33,34] that cover the range of acceleration amplitudes and frequencies required to capture human movement [254]. However commercial accelerometers have limitations, for example high frequency movement and noise information can escape the bandpass filter which in turn adds unexplained variation in activity counts [35]. In addition, variations in epoch length, cut points and device type further add to the lack of clarity in the literature [36-38]. This is further confounded by the fact that commercially available accelerometers only provide manufacturer-dependent output values that are computed by unpublished and proprietary signal processing techniques, resulting in a unit of measure termed, 'activity counts'. Activity counts summarize data in an epoch, reducing the burden of data management, analysis, and interpretation; however, information about the raw accelerometer signal is irretrievably lost and a full picture of physical activity overlooked. In the assessment of human movement, a central body position is the best accelerometer placement for capturing overall quantity of activity and best predicts energy expenditure [255,256]. However, the location of an accelerometer should be dependent on what researchers are attempting to investigate. Mannini, et al. [48] asserted that for gait quality characteristics, an ankle-mounted monitor had greatest validity, with a classification accuracy of 95%. Furthermore, detailed information about gait quality during ambulation, gait phase detection, walking speed estimation, with an ankle mounted device would be far more revealing [48,257].

The quantity of physical activity has been linked to various comorbidities, such as hypertension and obesity. [28,258] The quantity of physical activity is useful in studies interested in measuring energy expenditure. The problem is that energy expenditure takes one simple measure from the accelerometer trace, the area under the curve. In contrast, there are numerous other features that can be derived from accelerometer data. For example, quality characteristics can provide specific, contextualised feedback, but these have not been well utilised. The best-known use of raw accelerometry to ascertain qualities of movement is in fall detection and the mobile gait analysis of older adults [194,259,260] whereby specific monitoring of walking and balance quality has been used to determine patients' safety and control during ambulation. As novel and robust analytics develop quantity and quality data will be derived from accelerometer traces [257].

For example, fast Fourier transformation (FFT), has been used to process the accelerometer signal and identify gait qualities; walking smoothness, walking rhythmicity, dynamic stability and stride symmetry [18,19]. While FFT is an analytical technique used to characterise accelerometer data, cluster analysis involves the use of algorithms to separate a population into clusters or groups based on various parameters, such as activity behaviours, gait or movement qualities, stride profile, and BMI. Cluster analysis uses an iterative process of interactive, multi-objective optimization and has been used to inform animal movement and behaviour theory [208] and to identify and track cells [47]. Given the nature of human movement, cluster analysis could be of great use in the understanding and analysis of gait and movement quality characteristics at a group level [257].

Fast Fourier transformation and cluster analysis can be combined to analyse movement in standardised settings. Moreover, sensors can be attached to whole groups undertaking the same movement task. The multi-stage fitness test (MSFT) is a globally utilised test of cardio-respiratory, particularly used within school aged children, and is a component of the European battery of cardiorespiratory and motor tests [261]. It is well reported that obese children move less and with much greater difficulty than normal-weight counterparts [105-110]. This compromised movement is attributed to greater force through joints, decreased mobility, modification of gait pattern, and changes in the absolute and relative energy expenditures for a given activity. Further, detrimental changes in gait pattern have been demonstrated at the ankle, knee, and hip, and modifications at the knee level affecting articular integrity [104,105]. Although some recent work has examined the relationship between gross motor and fundamental movement skills and physical activity, in a standardised setting (incorporating accelerometry) [262,263], however, there has been no attempt in the literature to use clustering algorithms to profile and compare derivatives of a raw acceleration trace signal during standardised fitness tests. There is clearly potential to derive more information from the signal from accelerometers to address current gaps in scientific knowledge. The aims of this study were first, to apply automated, novel analyses to characterise the movement quality of children during the MSFT [47-49], and second, to report how movement quality characteristics of gait cluster according to BMI.

6.3 Methods

6.3.1 Participants and settings

One hundred and three children (10.3±0.6y, 1.42±0.08m, 37.8±9.3kg, body mass index; 18.5±3.3 kg·m^2) volunteered to take part in this study. Participants were a representative sub-sample of 822 children (10.5±0.6y, 1.42±0.08m, 27.3±9.6kg, body mass index; 18.7±3.5 kg·m^2) from 30 schools in the City and County of Swansea. Mean and variance data were not significantly different between the whole sample and sub-sample (*P*>0.05). The participants attended an indoor training facility, had anthropometric recordings taken and took part in the MFST. Additionally, children were classified as either underweight (<5th percentile, n = 7), normal weight (5th to 85th percentile, n = 73), overweight (>85th to <95th percentile, n = 14) or obese (≥ 95th percentile. n = 9) [213]. This research was conducted in agreement with the guidelines and policies of the institutional ethics committee.

6.3.2 Instruments and Procedures

After standard familiarisation and five minute warm-up, children performed the MSFT (Leger, et al. [264]), whilst wearing a custom built Micro Electro-Mechanical System (MEMS) based device, which incorporated a tri-axial accelerometer with a +/- 16g dynamic range, 3.9mg point resolution and a 13 bit resolution (with a z-axis amplitude coefficient of variation of 0.004 at 40hz) (ADXL345 sensor, Analog Devices). It was housed in a small plastic case and affixed via a Velcro strap to the lateral malleolar prominence of the fibula of the right leg and set to record at 40 Hz.

Anthropometrics

Standing and seated stature (measured to the nearest 0.01m) and body mass (to the nearest 0.1kg) were measured using a stadiometer (SECA, Hamburg, Germany), sitting stadiometer (Holtain, Crymych, UK) and digital scales (SECA, Hamburg, Germany), respectively, using standard procedures [212].

Twenty-metre Multi-Stage Fitness Test

Participants completed the MFST by running back and forth along a 20m course, and were required to touch the 20m line at the same time that a sound signal was emitted from a pre-recorded audio disk. The frequency of the sound emissions increased in line with running speed. The test stopped when the participant reached volitional exhaustion and was no longer able to follow the set pace, or participants were withdrawn after receiving two verbal warnings to meet the required pace [265].

6.3.3 Data analysis

Raw acceleration data was uploaded into MatLab (MATLAB version R2016a), where the subsequent movement quality characteristics; integrated acceleration, stride profile quotient, stride variability, stride frequency, stride angle, spectral purity, and time to volitional exhaustion were derived. The MSFT was broken down into its respective running speed section. The characteristics used for analysis were derived from acceleration in the axis along the lower leg towards the origin of motion, termed the radial axis, in addition, three complete gait cycles were removed from the analyses prior to and post the point of turning during the test to reduce the effect the altered gait pattern had on the overall analyses. The maximum impact force generated upon foot strike, F_{max}, corresponds to the peak positive value of acceleration (force vector pointing from foot to knee) and was calculated by subtracting the background static acceleration and multiplying by the participant's weight. The stride angle, α_{max} was obtained from the peak acceleration value in the negative direction. This point represented the maximum leg lift and when dynamic acceleration was zero, the radial acceleration was wholly determined by the vector component of the gravitational field, as determined by the angle of the accelerometer relative to the vertical axis. Therefore, determining the angle to which the subject's leg swings, the minimum point during the acceleration trace of the stride, A_{radial} was used in the following equation (Equation 7):

$$\alpha_{max} = acos(A_{radial}/g)$$

Equation 7. Maximum angle of foot lift

Where, α_{max} is the stride angle; $acos$ is the inverse of cosine; A_{radial}, is the minimum point during the acceleration trace of the stride; and g, is gravity.

The integrated acceleration was also determined, using an integration of the rectified signal and correspondent to the computation used to derive the standard 'activity counts' by other commercial devices [214].

Fundamental frequency was derived by first applying a discrete FFT to the data. The fundamental frequency of motion was identified as the highest amplitude component. The Stride Profile Quotient (Q), is a multi-dimensional measure derived from the mean stride frequency and mean stride angle of each child during the first and last section of running that each child completed. The absolute of the two measures between the two sections was derived and normalised. These values were then used in the following equation (Equation 8), where a score of *1* would equate entirely to changes in stride frequency, and a score of *0* would equate to changes entirely in foot lift angle.

$$Q = \sin(\operatorname{atan}(D1/D2))$$

Equation 8. Stride profile quotient

Where Q, is the stride profile quotient; $\sin$, represents the sine function; atan, represents the inverse of the tangent; $D1$, is the = absolute difference in frequency and $D2$, is the absolute difference in foot lift angle.

Spectral purity was calculated from the cumulative distribution function (CDF) of the frequency spectrum and is the gradient of the CDF at high frequency, i.e. it measures how tightly the frequency components of the gait cycle are distributed. Finally, time to volitional exhaustion (TTE), derived by converting events into seconds based on the sampling frequency (40 Hz) was also recorded as a measure of overall performance.

Cluster analysis

In order to carry out further analysis of the cohort and identify areas of interest within the sample we applied a clustering to the dataset. The derived characteristics (integrated acceleration, stride profile quotient, stride variability, stride frequency, stride angle, and spectral purity) from the raw acceleration traces (described above) were normalised so that they could be compared and input into an in-built clustering algorithm (MATLAB version R2016a). This algorithm goes through multiple iterative processes in order to cluster the data along the columns of the dataset. The similarity or dissimilarity between metrics was determined by calculating the pairwise Euclidean distances between the values of the different metrics.

$$d_{2st} = (x_s - x_t)(x_s - x_t)'$$

Equation 9. Euclidean distance

Where, d is the Euclidean distance; x_s and x_t represent the data values being compared.

Once the distances between the characteristics (integrated acceleration, stride quotient, stride variability, stride frequency, spectral purity, TTE, BMI) for each child were derived, a linkage function was applied, to determine the proximity of the metrics to each other. These were paired into binary clusters, which were subsequently grouped into larger clusters until a hierarchical tree was formed. The resulting clustergram was displayed in terms of a heat map and dendrogram. The height of the link at which two observations on the dendrogram were joined was analysed using cophenetic distance, to demonstrate the similarity between two clusters [46,215,216]. The values for the dendrogram linkages were subsequently normalised. The cophenetic distance ratio for the overall clustergram was also measured to demonstrate how successfully the dendrogram preserved the pairwise distances between the original unmodeled data points (where 1 is maximum). As data were not normally distributed non-parametric methods were used to analyse the data, and were presented as mean, median and upper and lower quartiles. The Kruskall-Wallis test was used to determine general differences between the various characteristics and the Mann-Whitney U test (with continuity correction and tie adjustment [266]) was used to determine specific differences between BMI groups. The Spearman's rho test was used to identify correlation coefficients between BMI within each characteristic. For all statistical tests an alpha level of 0.05 was applied. Data were reported in graphical and tabular format.

6.4 Results

The results from this study demonstrated that neither overall integrated acceleration nor overall stride variability were significantly different across BMI groups (Table 7, Figure 10, Figure 11).

There were significant differences found in TTE between UW and OB (P=0.03) and OB and NW (P=0.05) (Table 7, Table 8, Figure 10). The OB group had significantly lower spectral purity than every other group (OB and OW: P=0.02, OB and NW: P=0.01, OB and UW: P<0.001) (Table 7, Table 8). The OB group had significantly lower stride angle than NW (P=0.04) and UW (P=0.04) groups (Table 7). Further, stride profile quotient was significantly different between UW and NW (P=0.01) and UW and OB (P=0.03) (Table 7, Table 8, Figure 13).

Significant differences between BMI groups were found for stride profile quotient (P=0.03) and spectral purity (P=0.02). The clustergram illustrated that spectral purity and TTE (cophenetic distance: 0.3), stride profile quotient and BMI group (cophenetic distance: 0.6), and stride profile characteristics (integrated acceleration, stride angle and stride variability: cophenetic distance 0.57) were clustered together (Figure 5), with a cophenetic distance ratio for the overall clustergram of 0.86.

Following the Spearman's rho test, significant (P<0.05) relationships were found between integrated acceleration (r=-0.22), stride variability (r=-0.22), stride angle (r=-0.23), TTE (r=-0.25) and spectral purity (r=-0.24) and BMI.

Table 7. Differences in movement quality characteristics between BMI groups.

Group	Q	MRV	SV	SF	SA	TTE	SP
UW-NW	0.01*	0.30	0.23	0.99	0.59	0.26	0.21
UW-OW	0.07	0.17	0.15	0.36	0.15	0.09	0.11
UW-OB	0.03*	0.33	0.33	0.80	0.04*	0.03*	<0.001*
OB-NW	0.13	0.74	0.87	0.60	0.04*	0.05*	0.01*
OB-OW	0.16	0.87	0.51	0.51	0.87	0.33	0.02*
OW-NW	0.51	0.20	0.37	0.09	0.10	0.35	0.75

Q: Stride profile quotient, MRV: maximum radial velocity, SV: stride variability, SF: stride frequency, SA: stride angle, TTE: time to volitional exhaustion, SP: spectral purity. UW: underweight, NW: normal weight, OW: overweight, OB: obese, * denotes significant difference ($P \leq 0{,}05$).

Table 8. Descriptive data for time to exhaustion, spectral purity and stride profile quotient.

	Measure	**UW**	**NW**	**OW**	**OB**
	Mean	328	279	254	203
	Med	293	263	227	182
TTE (s)	UQ	402	352	288	258
	LQ	257	190	177	168
	Mean	2.97	2.91	2.90	2.80
	Med	2.95	2.9	2.89	2.8
SP	UQ	3.02	2.97	2.94	2.88
	LQ	2.93	2.81	2.84	2.71
	Mean	0.15	0.51	0.5	0.71
	Med	0.11	0.48	0.35	0.91
Q	UQ	0.25	0.88	0.86	0.99
	LQ	0.05	0.25	0.19	0.51

TTE: time to volitional exhaustion, SP: spectral purity, Q: stride profile quotient, UW: underweight, NW: normal weight, OW: overweight, OB: obese, Med: Median value, UQ: upper quartile value, LQ: lower quartile value.

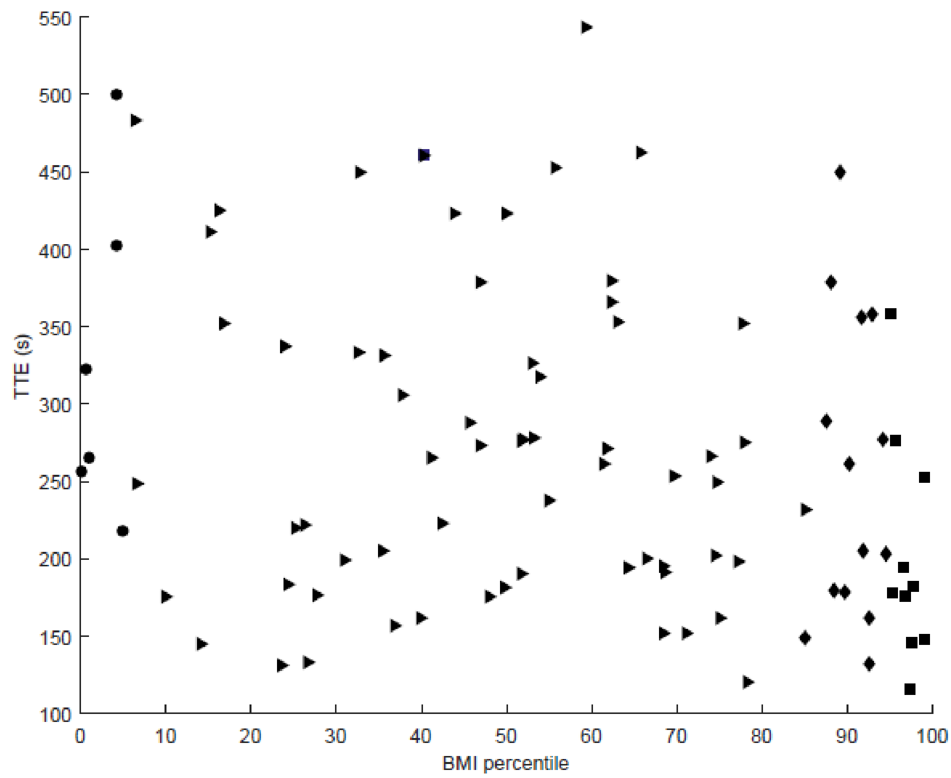

Figure 10. Body-mass Index vs. Time to Exhaustion (seconds). Filled black circles: Underweight children, filled black triangles: normal weight children, filled black diamonds: overweight children, filled black squares: obese children.

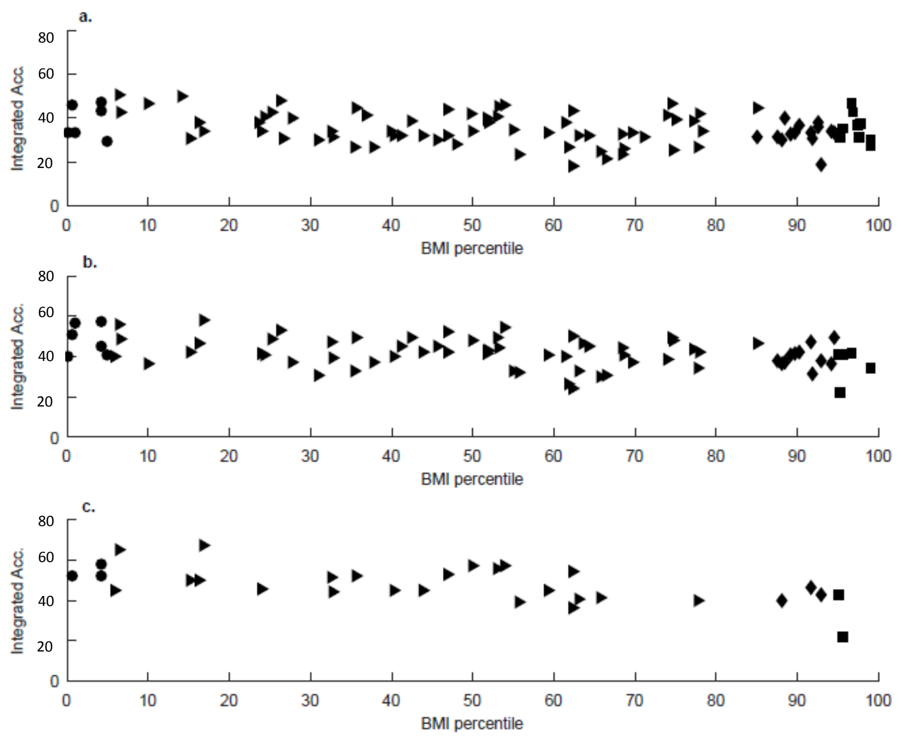

Figure 11. Integrated Acceleration vs. Body-mass index -a: 8.0km.h-1, b:9.5km.h-1, c:10.5km.h-1. Filled black circles: Underweight children, filled black triangles: normal weight children, filled black diamonds: overweight children, filled black squares: ob child

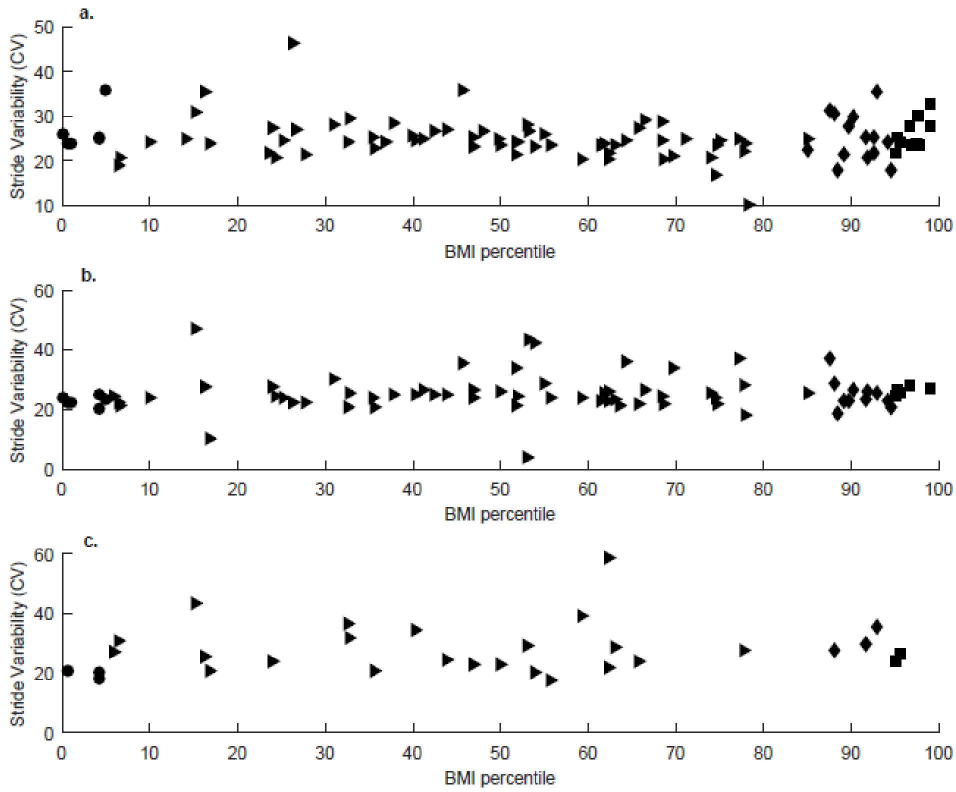

Figure 12. Stride variability (Coefficient of Variation) vs. Body-mass index - a: 8.0km.h-1, b:9.5km.h-1, c:10.5km.h-1. Filled black circles: Underweight children, filled black triangles: normal weight children, filled black diamonds: overweight children, filled black squares: obese children.

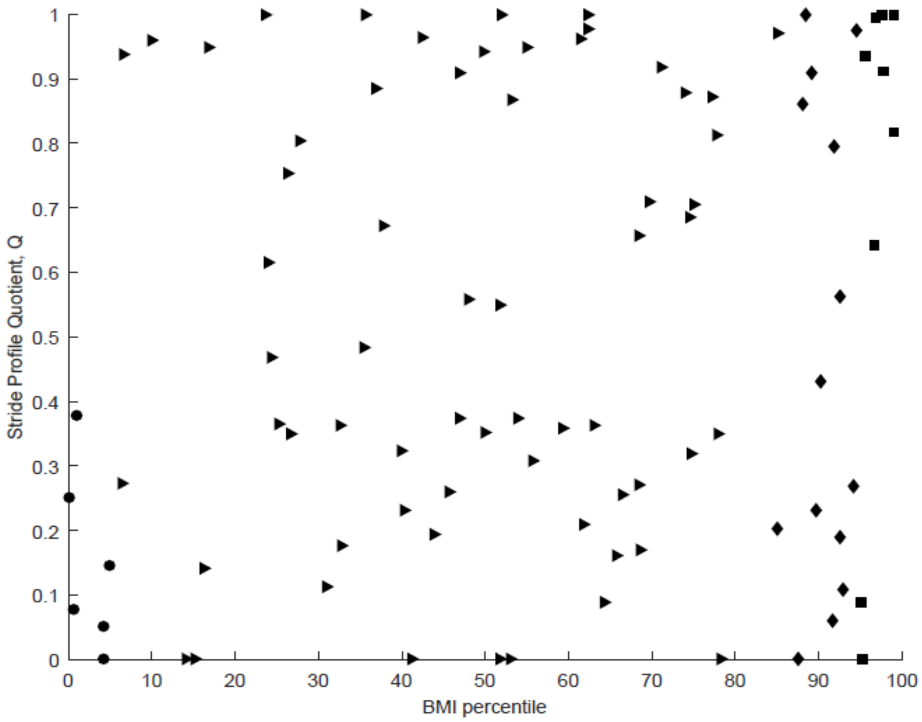

Figure 13. Stride profile quotient vs. Body-mass index. Filled black circles: underweight children, filled black triangles: normal weight children, filled black diamonds: overweight children, filled black squares: obese children.

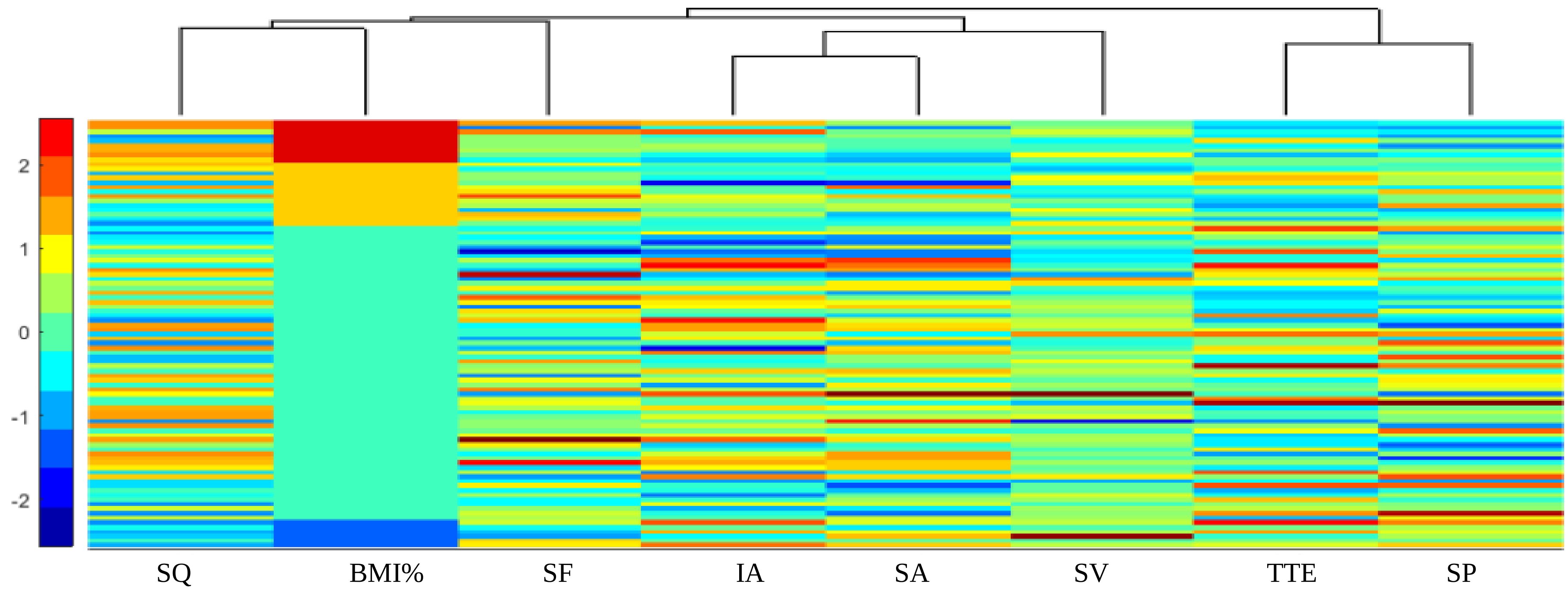

Figure 14. Clustergram and Dendrogram

Colours represent z-scores in the Clustergram. The Dendrogram highlights linkage between two or more characteristics. SQ: Stride profile quotient, BMI%: body-mass index percentile group, SF: stride frequency, IA: integrated acceleration, SA: stride angle, SV: stride variation, TTE: time to exhaustion, SP: spectral purity.

6.5 Discussion

The aims of this investigation were; first to characterise movement qualities using novel analyses of children performing the MSFT, and second, to report how these movement qualities of gait clustered according to BMI group.

The principal findings of this study were; that children from the OB group had significantly lower spectral purity than every other group and significantly lower TTE than UW and NW children. The clustergram linked TTE and spectral purity at a cophenetic distance of 0.3 and BMI and stride profile quotient at a cophenetic distance of 0.6. Further, significant negative correlation coefficients were found between BMI and TTE, spectral purity, integrated acceleration, stride angle and stride variability.

6.5.1 Clustergram overview

In order for a clustergram to be considered successful a cophenetic distance ratio of at least 0.75 is required. The clustergram in this study had a cophenetic distance ratio of 0.86, indicating confidence in the veracity of clusters identified. The clustering algorithm hierarchically linked each characteristic (integrated acceleration, stride profile quotient, stride variability, stride frequency, stride angle, spectral purity, and TTE), accordingly. The proximity of two or more characteristics within the clustergram indicated how closely the movement quality characteristics were linked to each other [46,215], for example BMI and stride profile quotient: 0.6, time until volitional exhaustion and spectral purity: 0.3. This cophenetic distance ratio indicated that movement characteristics can be successfully, and reliably, clustered.

6.5.2 Body-mass index, harmonic content and overall performance

The finding that higher BMI had lower overall TTE (Figure 10, Table 7), and by extension cardiovascular fitness, agrees with similar studies [267], and that obesity has a highly deleterious effect on fitness and motor skill development [268].

Our results are also novel. While spectral purity represents a measure of the motor control of ambulation [18,19], it has not been used in standardised fitness tests. Results from this study demonstrate that spectral purity, and performance score/fitness indicator (TTE) were cophenetically linked. Therefore, spectral purity is a characteristic of movement quality in children performing the MSFT (Figure 14).

Further the frequency and harmonic content of the accelerometer output derived from the MSFT, spectral purity, was negatively correlated with BMI ($r=-0.24$, $P=0.02$).

While the harmonic content of ambulation is related to movement quality [181,269], its relationship with BMI has not been reported in the literature. This is a novel finding and indicates that the frequency and harmonic content of ambulation, and by extension, performance (TTE) during the MSFT, differs by BMI.

This study indicated that overall performance during the MSFT, as well as the frequency and harmonic content of movement, differs by BMI group. This study shows spectral purity can be used as an indicator of overall performance, as well as being significantly related to BMI.

6.5.3 Body-mass index and stride characteristics

Stride frequency and stride angle may be independently used to provide an in-depth assessment of gait, in different age, body mass and gender groups. For higher BMI individuals, higher frequencies have been linked with greater knee-joint loads and deleterious to the biomechanics of ambulation [104,270]. The quotient metric we derived from stride frequency and angle to assess movement quality is reflective of children's running approach when performing the MSFT. This quotient has not yet been reported in the literature. We report that this stride profile quotient was an important contributor to the hierarchical clustering algorithm and was clustered with BMI (Figure 14).

The stride profile of children in different BMI groups illustrated contrasting approaches to the MSFT (Figure 13). The mean stride profile quotient for the BMI groups showed that NW and OW children altered their gait in an analogous fashion (NW: 0.5, OW: 0.51), indicating that these children responded to the stimulus of an increase in running speed during the MSFT by increasing stride angle and frequency. In contrast the stride profile quotient for UW and OB children presented different responses (UW: 0.15, OB: 0.71) whereby OB children, increased stride frequency but not stride angle. In addition, the clustergram provided a novel illustration of this finding, with children of NW/OW BMI displaying similarly low stride profile quotient scores, while the reverse occurred for OB children (Figure 14).

Children in the OB group predominantly altered stride profile through increases in stride frequency, as opposed to stride angle. Our findings that OB children develop a different gait have also been reported elsewhere, and has been shown to be exacerbated with increases in running speed [104,105,108]. The inability to alter stride angle is reflective of OB children's reduced articular range of motion in hip flexion, hip adduction, and knee flexion, compared to NW children [271]. The alteration in stride profile was associated with BMI (r=0.18, *P*=0.09).

Reduction or impairment in range of motion (ROM) would detrimentally affect movement quality and performance during the MSFT [104,105,271]. In fact, OB children, who displayed a greater stride profile quotient score, also had a significantly lower TTE than every other BMI group (Table 7, Table 8). This indicates that overall performance on a standardised fitness test may be effected by stride profile.

This work is supportive of laboratory based findings that OB children have an altered gait and impaired articular ROM; this is reflected by the in-field movement quality characteristic, stride profile quotient, and demonstrates that during a standardised fitness test, stride profile is linked to BMI.

6.5.4 Stride characteristics

Three stride characteristics, integrated acceleration, stride angle and stride variability were clustered together, at a cophenetic distance of 0.57. Spearman's rho test also demonstrated very similar relationships for all three characteristics with BMI (integrated acceleration: r=-0.22, *P*=0.02, stride angle: r=-0.23, *P*=0.03, stride variation: r=-0.22, *P*=0.03) The weak negative correlation coefficient between BMI and integrated acceleration is also supported by previous literature, where OB children have been shown to move less and with greater difficulty than their NW counterparts [106], in addition to demonstrating a reduced velocity compared to NW children [106,111,272]. The difficulty in movement in OB compared to NW children is also reflected in their inability to effectively alter stride angle, which further diminishes TTE.

Although similar relationships were found between integrated acceleration, stride angle and stride variability with BMI (Table 7), there were underlying differences between these characteristics. Stride angle was found to be significantly different between OB and UW, and OB and NW (Table 1). Further, despite the significant relationship between integrated acceleration and BMI, it was not significantly different between groups (Table 1, Figure 2). Neither were there any significant differences in stride variation between any groups (Table 7, Figure 12).

The movement quality characteristics of integrated acceleration, stride angle and stride variability were close cophenetically linked characteristics, as illustrated in the clustergram (Figure 5) These data provided novel insights into children's movement quality when performing the MSFT. For example, although stride angle was significantly different between OB and NW and OB and UW children, the quantity and variability remained consistent across BMI groups (Table 7, Figure 13). Furthermore, although high stride frequency affected gait in obese children [106], this study did not find any statistical differences between BMI group for stride frequency or stride variation (Table 7, Figure 12). Therefore, neither stride frequency, nor stride variation, precluded high TTE in the MSFT. Stride angle appears to play a pivotal role in the stride profile and performance of children taking part in the MSFT. In conclusion, multiple characteristics drawn from an accelerometer signal can be used to build a broader picture of children's movement quality during a standardised fitness test and these may also be applicable to measures of habitual physical activity.

6.5.5 Limitations

There were a number of limitations to this study. First the clustering algorithm was structured using hierarchical methods pairing characteristics by proximity. However, this means it may not be instinctively obvious if characteristics are anti-correlated, for instance there was a clear negative association between BMI and spectral purity. On the other hand, this can be overcome with careful interpretation of the clustergram and in addition to other correlation analyses (i.e. Spearman's rho). This study sought to employ novel analysis techniques to assess movement quality characteristics, and although TTE was recorded, no inferences to physiologic outputs (e.g. estimated $\dot{V}O_{2max}$, peak $\dot{V}O_2$, heart rate variability) or psychological aspects were made as this was beyond the scope and aims of the study. Finally, this study did not incorporate analysis of gait characteristics at the point of turning, there is body of literature specifically investigating turning strategy and including it in our analyses would have detrimentally impacted mean and standard deviation values and thus, the authors recommend that this be investigated further.

6.6 Conclusion

The first aim of this study was to apply automated, novel analyses to characterise the movement quality of children during the MSFT. This investigation found that key gait characteristics of children's running performance during the MSFT could be derived.

The second aim was to report how movement quality characteristics of gait cluster according to BMI. This study has shown clustering between a performance/fitness outcome, frequency and harmonic content of movement and BMI during a standardised fitness test and, that movement quality in children of higher BMI (OB), is characterised by significantly lower stride angle, significantly lower TTE and significantly lower spectral purity than OW, NW and UW counterparts.

Finally, further investigations into age, gender and movement characteristics other than running are required before the relationship between movement quality characteristics and performance/fitness in children can be elucidated. This research will provide further insights into the development of physical competency and fitness in children.

6.7 Summary: Experimental Chapter Two

The aims of this experimental chapter were to characterise the movement quality of children performing a standardised fitness test, and report how movement quality characteristics cluster according to weight status.

Accordingly, obese children were found to have significantly lower spectral purity than every other group, in addition to significantly lower time to exhaustion (TTE) than UW and NW children ($P<0.05$). Weight status was clustered with stride profile, and TTE with spectral purity. Significant negative correlations ($P<0.05$) were found between BMI and TTE (r=-0.25), spectral purity (r=-0.24), integrated acceleration (r=-0.22), stride angle (r=-0.23) and stride variability (r=-0.22).

Overall, this was the first empirical study to report the spectral purity of children's gait. Further analysis unveiled key performance characteristics that differed between BMI groups which were representative of children's performance during a standardised fitness test, and significantly negatively correlated with BMI. This study was able to demonstrate that by analysing the raw accelerometer signal using novel analytics, hitherto unreported information could be revealed and warrants further investigation.

The subsequent experimental chapters of this thesis will aim to analyse and characterise movement quality characteristics in children during un-controlled activity, i.e. recess or free-play.

Thesis map

Chapter	Study		Outcomes
1	SlamTracker Accuracy under Static and Controlled Movement Conditions	*Aim*	To quantify the mean, standard deviation and variance of the SlamTracker device at a range of speeds
		Key Findings	Sample variance was <0.001g across all speeds and axes during the movement condition tests. In conclusion, the SlamTracker is shown to be an accurate and reliable device for measuring the raw accelerations of movement.
	Validity of Force and Angle Derivation Using Raw Accelerometry	*Aim*	To verify the validity of using raw accelerometry to estimate force (N) and leg angle (°) during ambulation.
		Key Findings	Angle estimation (°) and force derivation (N), using an accelerometer, significantly correlated with video verified angle estimation (r=0.98, p=0.001) and force platform verified values (r=0.98, p=0.001), respectively.
	A Kinematic Analysis of Fundamental Movement Skills	*Aim*	To characterise the relationship between facets of fundamental movement and, to characterise the relationship between overall integrated acceleration and three-dimensional kinematic variables whilst performing fundamental movement skills.
		Key Findings	Overall integrated acceleration was comparable between participants (CV: 10.5), whereas three-dimensional variables varied by up to 65%. Indicating that although overall activity may be correspondent, the characteristics of a child's movement may be highly varied.
2	Profiling Movement Quality and Gait Characteristics According to Body-Mass Index in Children (9-11y)	*Aim*	To apply automated, novel analyses to characterise the movement quality of children during the multi-stage fitness test, and to report how movement quality characteristics of gait cluster according to BMI
		Key Findings	OB children had significantly lower spectral purity and time to exhaustion (TTE) than UW NW, and OW children (*P*<0.05). BMI was clustered with stride profile, and TTE with spectral purity. Significant negative correlation (*P*<0.05) between BMI and; TTE (r=-0.25), spectral purity (r=-0.24), integrated acceleration (r=-0.22), stride angle (r=-0.23) and stride variability (r=-0.22). Spectral purity was representative of children's performance during the MSFT.
3	Profiling Movement Quality and Gait Characteristics of Recess Activity in 9-11-year-old Primary School Children	*Aim*	To characterise children's recess physical activity, and investigate how movement quality characteristics of gait cluster during school recess
		Key Findings	-
4	Profiling Movement and Gait Characteristics in Early-Years Children (3-5y)	*Aim*	-
		Key Findings	-

7.0 Experimental Chapter 3

7.1 Profiling Movement Quality and Gait Characteristics of Recess Activity in 9-11-year-old Primary School Children

*this chapter is an accepted manuscript: Clark, C. C. T., Barnes, C. M., Holton, M. D., Summers, H. D., Mackintosh, K.A., Stratton, G. (*in press*). Profiling movement quality and gait characteristics according to body-mass index in children (9–11 y). *Human Movement Science*.

7.2 Introduction

Regular physical activity during childhood is associated with a lower risk of obesity, insulin resistance, mental health problems, cardiovascular disease, and improved academic performance [5,16,273]. However, a substantial number of children fail to engage in sufficient physical activity outside of school [146,274-276]. Children spend a significant proportion of their waking time at school, and noncurricular time, such as school recess periods, provide opportunities for children to be physically active within the school environment [137,138]**.** It is suggested that recess periods may provide the single greatest opportunity during the school day to impact on child physical activity levels [109,139,140].

A number of systematic reviews have examined correlates of children's physical activity [144-146], yet these have predominantly focused on factors associated with whole-day activity. Ridgers, et al. [277] and Brusseau, et al. [278] highlighted that overall recess physical activity remains statistically invariant day-to-day, no significant main effects for moderate-to-vigorous activity, and no significant differences in recess activity between *a priori* categorised low and high activity children [279]. On the other hand, physical activity is a multidimensional behaviour influenced by numerous factors across several domains [147], and Myer, et al. [280] highlighted that overall activity measures overlook critical information, such as; skill development, enjoyment and, importantly, movement quality.

There is a paucity of suitable metrics available to objectively examine movement quality of children's physical activity, in-field. It has recently been asserted that novel analytics may bridge the gap between quality and quantity measures of human movement [32]. Traditional linear measures, such as mean and standard deviation, are measures of centrality and thus provide a description of the amount or magnitude of the variability around a central point, such as overall physical activity levels [44]. However, the use of such measures assumes that movement or activity variations are random and independent [281]. Contrastingly, previous studies have highlighted that such variations are distinguishable from noise, are biologically relevant and warrant further investigation [44,282-285].

Accelerometers that record the raw signal without undergoing propriety pre-processing have been used to provide specific monitoring of walking [194,259,260], and to assess characteristics such as ambulation smoothness, control, balance and rhythmicity [18,19]. Furthermore, frequency-domain features, extracted from the coefficients of raw accelerometry signals may be obtained by performing spectral analysis (usually fast Fourier transformation (FFT)), where the values of the coefficients represent the amplitudes of the corresponding frequency components. Both the dominant frequency, its amplitude, and spectral entropy, a product of spectral analysis, have been commonly used as the frequency-domain features for physical activity energy expenditure estimation and activity type [286-290].

In addition to frequency-domain features, coefficient of variation (CV) in temporal data has been used to improve activity type estimation. Pivotal works by Crouter and colleagues [135,255,291-294] have demonstrated that, accelerometry derived, activity count CV can be used to distinguish between running and walking, and improve energy expenditure estimation when incorporated into regression models.

However, whilst novel measures have been used to quantify physical activity energy expenditure and its classification, less attention has been given to the *quality* of movement. Movement quality characteristics are retrievable using the harmonic content of the accelerometer signal, by analysing the symmetry within a movement, exploiting the periodicity of the signal [295,296]. The resulting spectral purity and integrated accelerations of each movement can be analyzed to assess, and profile, movement quality in children [18,218,297]. This type of analysis is highly suggestive of a fundamental feature of the neural control of movement [44] and shown to be representative of movement quality in standardised settings [218]. However, this has not been applied to children’s activity in an uncontrolled setting, such as school recess.

The aims of this study were to characterise children's recess physical activity, and investigate how frequency spectrum movement quality characteristics cluster during school recess.

7.3 Method

7.3.1 Participants and settings

Twenty-four children (18 boys) (10.5±0.6y, 1.44±0.09m, 39.6±9.5kg, body mass index; 18.8±3.1 $kg{\cdot}m^2$) volunteered to take part in this study from a primary school in the U.K. Participants were a representative sub-sample of 822 children (10.5±0.6y, 1.42±0.08m, 27.3±9.6kg, body mass index; 18.7±3.5 $kg{\cdot}m^2$) from 30 primary schools and there were no significant differences for any descriptive characteristics between the whole sample and sub-sample ($P>0.05$). Prior to research commencing, informed consent and child assent was attained. This research was conducted in agreement with the guidelines and policies of the institutional ethics committee.

7.3.2 Instruments and Procedures

Children took part in a normal school-time recess period (40 ± 4 minutes per day) for one school week (five days), and activity was recorded using a Micro Electro-Mechanical System (MEMS) based device [220,298], which incorporated a tri-axial accelerometer with a ± 16g dynamic range, 3.9mg point resolution and a 13-bit resolution (ADXL345 sensor, Analog Devices). The recording frequency was set to 40 Hz, and deemed appropriate based upon the work of Clark, et al. [230], where amplitude coefficient of variation was optimal (0.004%) at 40 Hz. In order to standardise data collection, the MEMS device was housed in a small plastic case and affixed via a Velcro strap to the lateral malleolar prominence of the fibula of the right leg of all participants. Mannini, et al. [48] highlighted that for movement quality characteristics related to ambulation, an ankle-mounted monitor may be most suitable, and Barnes, et al. [299] systematically demonstrated that ankle affixed accelerometers can be used to accurately compute leg lift angle. Data were stored locally on the device and there were no incidences of data loss. Children were also asked to rank how they self-perceived their health and fitness, administered according to validated Likert scales: Idler, et al. [300] and Marques, et al. [301] (Self-reported health) and Ortega, et al. [302] (Self-reported fitness).

Anthropometrics

Stature (measured to the nearest 0.01m) and body mass (to the nearest 0.1kg) were measured using a stadiometer and digital scales (SECA, Hamburg, Germany), respectively, using standard procedures [212]. Additionally, children were classified as either underweight (<5th percentile), normal weight (5th to 85th percentile), overweight (>85th to <95th percentile) or obese (≥ 95th percentile) [213].

7.3.3 Data analysis

Raw acceleration data were extracted from the MEMS device and subsequently uploaded into MatLab (MATLAB version R2016a), where integrated acceleration and spectral purity were derived. The characteristics used for analysis were derived from acceleration in the axis along the lower leg towards the origin of motion, termed the radial axis. The integrated acceleration was determined using a full-wave rectification of the integrated raw acceleration signal and correspondent to the computation used to derive activity counts by other commercial devices (i.e ActiGraph, see: van Hees, et al. [214]).

Accelerometer data taken from children performing varying forms of ambulation were converted from the time into the frequency domain. In order to convert the data into the frequency domain the Fast Fourier transform was applied to the data. The Fast Fourier Transform computes the discrete Fourier transform (DFT) of a sequence.

Let x_0,…,x_(N-1) be a sequence of N complex numbers. The Fast Fourier transform computes the Discrete Fourier transform

$$X_k = \sum_{n=0}^{N-1} x_n . e^{-i2\pi kn/N} , k \in Z$$

Equation 1. Fast Fourier Transform

Where, N = number of time samples, n = current sample under consideration (0 .. N-1), x_n = value of the signal at time n, k = current frequency under consideration (0 Hertz up to N-1 Hertz), X_k = amount of frequency k in the signal (amplitude and phase, a complex number), n/N is the percent of the time gone through, 2 * pi (π) * k is the speed in radians·sec^{-1}, e^-ix is the backwards-moving circular path.

In order to determine the quality of a child’s movement - ‘Spectral purity’ was calculated from the cumulative distribution function (CDF) of the frequency spectrum. The CDF plot is used to generate a value for spectral purity. The empirical CDF *F(x)* is defined as the proportion of X values less than or equal to some value *x*. In this case, it is the number of values less than or equal to some frequency in a spectrum being considered. A measure for spectral purity is therefore considered to be the frequency at which the midway point of the CDF (0.5) occurs. As a result, spectra that is 'clean', i.e. consisting of a tall narrow peak at the fundamental frequency and only low amount of noise and small harmonics will have a different value to spectra where there is lots of noise, a shorter wider peak, and higher peaks at the harmonics. Spectral purity measures how tightly the frequency components of the raw accelerations are distributed using fundamental frequency to harmonics and the frequency spectrum analysis is directly related to the ambulation of a participant [218,299]. A participant could have high spectral purity and low overall activity, which indicates that cyclical, high periodicity movement has occurred. However, in combination with low integrated acceleration this equates to the participant remaining static, for example, sat down in one location for prolonged periods.

2.3.1 Cluster analysis

Cluster analysis is an analytic procedure that reduces complex multivariate data into smaller subsets or groups. Compared with other data reduction methods, such as factor analysis, clustering yields groupings that are based on the similarity of whole cases, as opposed to the individual variables that comprise those cases [45]. Cluster analysis is used for profiling, or in the development of classification systems or taxonomies [45,46]. Numerous characteristics of movement and lifestyle in adults and children (9-11y) can be reliably analysed using cluster analysis [47,215,218]. Further, Clark, et al. [32] highlighted that cluster analysis is an analytical tool that should be exploited in the analysis of human movement characteristics.

The derived characteristics (integrated acceleration, integrated acceleration coefficient of variation (CV), spectral purity, spectral purity CV, BMI percentile, self-perceptions of health and fitness, gender) were normalised to fall between the data range of 0 and 1, so that they could be compared and input into an in-built clustering algorithm (MATLAB version R2016a). This algorithm goes through multiple iterative processes to cluster the data along the columns of the dataset. The similarity or dissimilarity between metrics was determined by calculating the pairwise Euclidean distances between the values of the different metrics.

$$d_{2st} = (x_s - x_t)(x_s - x_t)'$$

Equation 2. Euclidean distance

Where, d is the Euclidean distance; x_s and x_t represent the data values being compared.

Once the distances between the characteristics for each child were derived, a linkage function was applied, to determine the proximity of the metrics to each other. The characteristics were paired into binary clusters, which were subsequently grouped into larger clusters until a hierarchical tree was formed. The resulting clustergram was displayed in terms of a heat map and dendrogram and were displayed in terms of Z-score, derived using a standard formula: Z = (raw score - mean) / standard deviation. The height of the link at which two observations on the dendrogram were linked is termed the cophenetic distance, which demonstrates the similarity between two, or more, clusters [46,215,216]. The values for the dendrogram cophenetic distances were subsequently normalised (0 to 1). The cophenetic distance ratio for the overall clustergram was also measured to demonstrate how successfully the dendrogram preserved the pairwise distances between the original unmodeled data points (where 1 is maximum).

The whole raw acceleration signal was analysed over the duration of each recess period, for each day (five in total), subsequently mean integrated acceleration and spectral purity values for each day were assessed for differences. A Shapiro-Wilk test was conducted to assess normality of distribution, and data were found to be significantly different from normal (all $P<0.05$). Therefore, non-parametric analyses were used, and were presented as mean, median and upper and lower quartiles. In order The Kruskall-Wallis (KW) and post-hoc Mann-Whitney U tests, with continuity correction and tie adjustment [266], were used to determine differences between days, where appropriate. The Spearman's rho test was used to identify correlation coefficients between each characteristic. All inferential statistics were performed using MatLab (MATLAB version R2016a) and statistical significance was accepted at $P\leq0.05$. Data were reported in graphical and tabular format.

7.4 Results

There were no significant inter-day differences found for integrated acceleration (*P*>0.05), however, significant inter-day differences were found for spectral purity derived movement quality (*P*<0.001). Post-hoc tests revealed significant differences between multiple days (detailed in Table 9). Significant, positive and negative, relationships were found between movement characteristics, and are detailed in Table 10.

The clustergram illustrated that integrated acceleration and mean spectral purity (cophenetic distance (CD): 0.22), integrated acceleration and self-perceived fitness/self-perceived health (both; CD: 0.22), mean spectral purity and self-perceived fitness/self-perceived health (both; CD: 0.13), self-perceived health and self-perceived fitness (CD: 0.02), gender and BMI percentile and integrated acceleration CV (CD: 0.90), and finally, BMI percentile and integrated acceleration CV (CD: 0.72), were clustered together (Figure 15), with a cophenetic distance ratio for the overall clustergram of 0.96.

Table 9. Descriptive data for integrated acceleration and spectral purity day-to-day variation

	Measure	**Day 1**	**Day 2**	**Day 3**	**Day 4**	**Day 5**
IA	Mean	8.86	9.09	10.76	9.73	10.32
	Med	8.69	8.61	10.77	9.93	10.12
	UQ	11.71	9.97	13.71	12.19	12.78
	LQ	6.35	7.37	8.17	7.39	8.14
SP	Mean	2.38	2.46 *	2.41 #	2.47 *	2.67 *, #, ϕ, ǂ
	Med	2.38	2.47 *	2.42 #	2.48 *	2.82 *, #, ϕ, ǂ
	UQ	2.41	2.53 *	2.47 #	2.52 *	2.9 *, #, ϕ, ǂ
	LQ	3.32	2.41 *	2.34 #	2.39 *	2.56 *, #, ϕ, ǂ

IA: mean Integrated acceleration, SP: mean Spectral purity, Med: Median, UQ: Upper quartile, LQ: Lower quartile. * denotes significant difference vs. day 1, # denotes significant difference vs. day 2, ϕ denotes significant difference vs. day 3, ǂ denotes significant difference vs. day 4. Significance level; *P*≤0.05.

Table 10. Correlation coefficient matrix for movement characteristics

	IA	IA CV	SP	SP CV	BMI %	SH	SF	Gender
IA	-	-0.05 *(0.82)*	0.51 *(0.01)* #	0.12 *(0.58)*	-0.55 *(0.005)* #	0.54 *(0.009)* #	0.47 *(0.02)* *	-0.09 *(0.66)*
IA CV	-	-	-0.02 *(0.92)*	-0.07 *(0.75)*	0.06 *(0.77)*	-0.01 *(0.97)*	-0.001 *(0.99)*	-0.19 *(0.37)*
SP	-	-	-	0.19 *(0.39)*	-0.05 *(0.79)*	0.65 *(<0.001)* ǂ	0.50 *(0.01)* #	-0.32 *(0.13)*
SP CV	-	-	-	-	0.11 *(0.62)*	0.22 *(0.31)*	-0.13 *(0.53)*	-0.08 *(0.72)*
BMI%	-	-	-	-	-	-0.53 *(0.007)* #	-0.53 *(0.008)* #	-0.002 *(0.99)*
SH	-	-	-	-	-	-	0.68 *(<0.001)* ǂ	-0.22 *(0.31)*
SF	-	-	-	-	-	-	-	-0.28 *(0.19)*
Gender	-	-	-	-	-	-	-	-

Data reported as r value (*P value*). * denotes significance at $P \leq 0.05$. # denotes significance at $P \leq 0.01$. ǂ denotes significance at $P < 0.001$. IA: Integrated acceleration, IA CV: Integrated acceleration coefficient of variation, SP: Spectral purity, SP CV: Spectral purity coefficient of variation, BMI%: Body-mass index percentile, SH: Self-perceived health, SF: Self-perceived fitness.

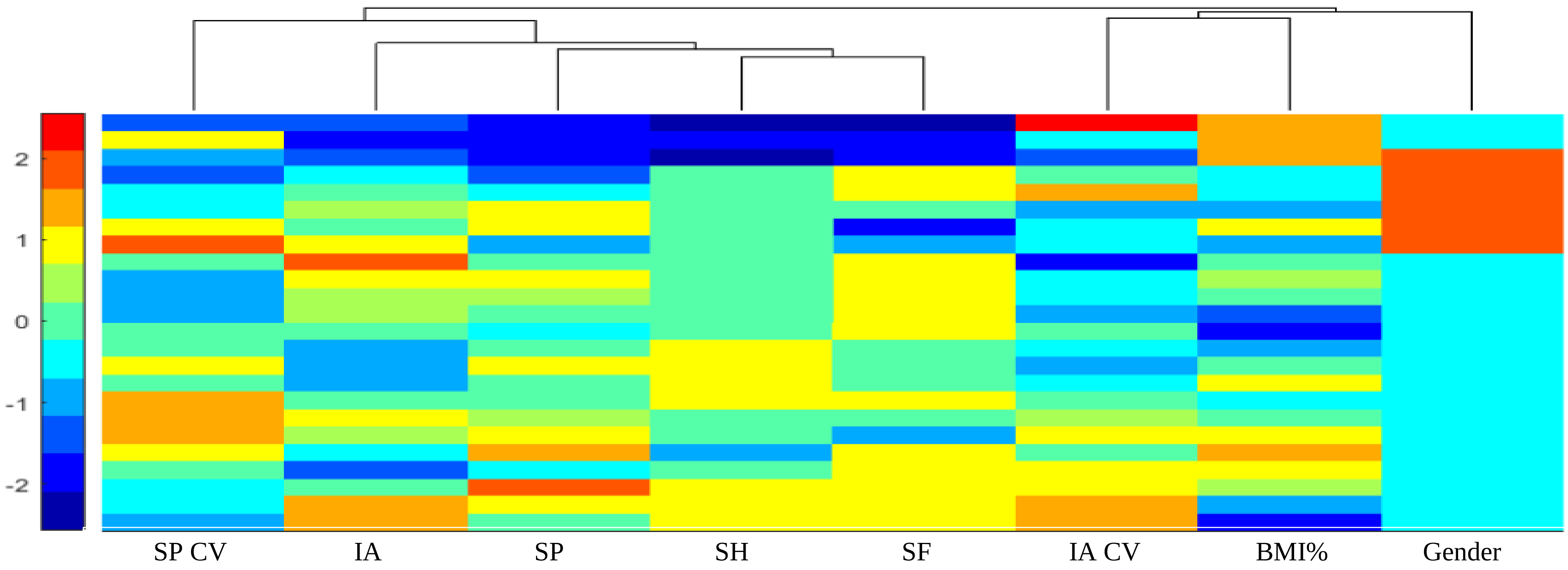

Figure 15. Clustergram and Dendrogram

Colours represent z-scores in the Clustergram (for Gender, blue denotes male and orange, female). The Dendrogram highlights linkage between two or more characteristics. SP CV: spectral purity coefficient of variation, IA: integrated acceleration, SP: spectral purity, SH: self-perceived health, SF: self-perceived fitness, IA CV: integrated acceleration coefficient of variation, BMI%: body-mass index percentile

7.5 Discussion

The aims of this study were to characterise children's recess physical activity, and investigate how movement quality characteristics of gait cluster during school recess.

The principal findings of this study were that although integrated acceleration did not differ significantly by day (P>0.05), spectral purity did (P<0.05). Key linkages identified by the clustergram were; integrated acceleration and spectral purity (CD: 0.22), integrated acceleration and self-perceived fitness and health (CD:0.22), spectral purity and self-perceived fitness and health (CD: 0.13). Further significant positive correlation coefficients were identified between integrated acceleration and; spectral purity, self-perceived health, and self-perceived fitness. Whilst, significant negative correlation coefficients were identified between integrated acceleration and BMI percentile.

7.5.1 Clustergram overview

In order for a clustergram to be considered successful a cophenetic distance ratio of 0.75 is required [303]. The clustergram in this study had a cophenetic distance ratio of 0.96, indicating confidence in the veracity of clusters identified. The proximity of two or more characteristics within the clustergram indicated how closely the movement quality characteristics were linked to each other, otherwise termed, the cophenetic distance [46,215]. For example, integrated acceleration and spectral purity: 0.22, spectral purity and self-perceived health: 0.13. The clustergram may also be visually inspected (Figure 1), where all values are expressed in colours, according to their z-score. For instance, in adjacent columns of the clustergram are points at which the colours, or z-scores, are matched (in particular integrated acceleration and spectral purity, and, spectral purity and self-perceived health), the degree to which the colours match provides an immediate, visual analysis of the clusters identified.

7.5.2 Integrated acceleration and spectral purity

Physical activity levels have previously been reported to be invariant day to day and insensitive to differences between *a priori* classified low and high activity children [279]. The present study supports this characterisation of recess, where integrated acceleration does not change significantly throughout the school week. On the other hand, novel characterisation of recess activity in this study, through spectral purity derived movement quality, highlighted significant day-to-day variance (Table 9). Congruent with previous research, the present study found that children's physical activity during recess can be characterised as comparable across days [277,279]. Importantly, recess activities are volitional, though results reported in the literature suggest that children are consistent in their choices due to factors such as playground hierarchies that dictate activity choices. Thus impacting upon the variability recorded, making recess characterisation using traditional methods relatively straightforward [277]. Advancing on previous research, the present study utilised analyses of the entire raw accelerometry signal, rather than the use of long epochs (> 5 s). Long epochs may be too insensitive to accurately characterise sudden bouts of activity, and concomitant frequency spectrum characteristics, thereby enhancing fidelity and accuracy in the present study [218,299].

Despite overall activity remaining invariant in a contextualised setting, movement quality characteristics are shown to be significantly different in the literature (Clark, et al. [218,304]). The present study found that spectral purity derived movement quality was significantly different day-to-day ($P \leq 0.05$) (Table 9). This finding supports Clark, et al. [304] who identified, through kinematic and accelerometric analyses, that quality of movement in standardised settings is significantly different in children (9-11y). Further, it has been highlighted that spectral purity derived movement quality is indicative of movement quality characteristics, such as time to exhaustion, overall activity, stride angle and stride frequency, all specifically relating to ambulation [218]. This novel finding demonstrates that the periodicity of the signal is variable day-to-day, indicating that the activities and length of specific activities changes daily, even though overall activity remains invariant, offering novel insight into recess characterisation on a group and individual basis. Further, a tentative interpretation of spectral purity derived movement quality is that fundamental frequency and harmonic characteristics measured from an ankle worn accelerometer reflect the ambulatory movement quality of children. Contextually, the signal characteristics of children's movement were significantly better on Day 5 vs. Day 1, whilst overall activity remained invariant. This has important implications given variability is intrinsic in all biological systems [44] and has been asserted that an optimal state of variability that exhibits chaos is important for health and functional movement [305,306]. In a comprehensive review, Stergiou, et al. [44] reported that variability has an optimal chaotic structure and deviations from this state can lead to biological systems that are either overly rigid and robotic or unstable. Both result in systems (humans) that are less adaptable to perturbations, such as those associated with unhealthy states or absence of skilfulness or control. It was also concluded that novel exploration of movement will provide a platform for better understanding human movement [44]. Significant ($P \leq 0.05$) relationships were found between integrated acceleration and mean spectral purity (r=0.51) using traditional correlation analyses, further, integrated acceleration and spectral purity were hierarchically clustered together at a cophenetic distance of 0.22 (Figure 15). Based upon previously reported cophenetic distances between characteristics of movement [218], this finding supports the notion that the underlying frequency spectrum is fundamentally important to overall physical activity levels.

Table 9 highlighted that spectral purity derived movement quality may be significantly better or worse daily, this finding has important practical implications related to physical activity intervention monitoring, at a group and individual level. Metcalf, et al. [307] reported that physical activity interventions, assessed using objective measures, were ineffective, however, no movement quality, nor frequency domain, measures were used in this meta-analysis. There is potential for future research to consider overall activity levels in conjunction with spectral purity (and other frequency spectra) derived movement quality measures to better elucidate intervention effectiveness and the underlying factors of human movement.

7.5.3 Body-mass index, gender and self-perception

Clark, et al. [218] previously demonstrated that integrated acceleration is significantly correlated with BMI in 9-11-year-old children taking performing the 20-m multi stage shuttle run test. Data in the present study found a significant negative correlation (r=-0.55) between overall activity and BMI. In Clark, et al. [218], the activity followed a standardised protocol, meaning that although the correlation to BMI was reported as significant, it was not strong. However, due to the uncontrolled nature of the present study, i.e. there were no predefined activities participants were completing, there were more degrees of freedom for weight status to impact upon overall activity. Significant ($P \leq 0.05$) relationships were found between mean integrated acceleration and; BMI percentile (r=-0.55), self-perceived health (r=0.52) and self-perceived fitness (r=0.47). Whilst BMI percentile was significantly correlated with; self-perceived health (r=-0.53) and self-perceived fitness (r=-0.53). Seabra, et al. [308] reported children with high BMI have lower levels of attraction to physical activity, lower perceived physical competence and less parental physical activity support, which puts them at greater risk of being physically inactive. Whilst, De Meester, et al. [309] asserted a combination of high actual and perceived motor competence is related to higher physical activity and lower weight status. Additionally, in the present study, self-perceived health was significantly correlated with self-perceived fitness (r=0.68), whilst being clustered at a cophenetic distance of 0.02 (Figure 15). This is correspondent to the work of Peterson, et al. [310] who showed self-reported lifestyle and fitness were strongly positively correlated.

Congruent with Stodden, et al. [22], i.e. perceived motor competence, actual motor competence, cardio-respiratory fitness and physical activity interact, and can lead to a positive or negative spiral of (dis)engagement in active lifestyles [22]. This study found that overall activity, weight status and self-perception of health and fitness were inter-related and fit within the developmental model proposed by Stodden, et al. [22]. This assertion may be further supported by the significant relationships found between spectral purity derived movement quality and; self-perceived health (r=0.65) and self-perceived fitness (r=0.5). Spectral purity was further shown to have a stronger correlation and closer cophenetic distance (Figure 15) to self-perceptions of health and fitness, than overall activity. This novel finding indicates that the frequency spectrum derived movement quality is more related to self-perceptions (of health and fitness) than a proxy measure of overall activity (integrated acceleration). Clark, et al. [218] and Barnes, et al. [299] have previously demonstrated spectral purity is a key characteristic of movement quality in a standardised setting, and it is evident that this translates to a measure of movement quality in uncontrolled recess activity.

In early childhood (3–5 years), it is expected that children's perceived motor competence will not strongly correlate with their actual motor competence or physical activity levels [309,311,312], and will generally overestimate their competence levels [23,309]. However, as children continue to develop during childhood (up to 12y) they become more accurate in assessing their own motor competence, resulting in stronger correlations between actual and perceived motor competence [23,309]. Therefore, in the age group utilised in this study (9-11y) it is conceivable that spectral purity derived movement quality is reflective of self-perceived competency relating to health and fitness.

7.5.4 Limitations

The clustering algorithm used in this study was structured using hierarchical methods pairing characteristics by proximity, meaning inverse relationships may be difficult to highlight. On the other hand, this can be overcome with careful interpretation of the clustergram, in addition to other correlation analyses (i.e. Spearman's rho). The sample size utilised within this study was relatively small, however incorporated all of the 9-11y population in the sample school, furthermore participants were a representative sub-sample of 822 children (10.5±0.6y, 1.42±0.08m, 27.3±9.6kg, body mass index; 18.7±3.5 kg.m2) from 30 schools, where mean and variance data were not significantly different between samples (*P*>0.05). It would be recommended, however, that a greater number of participants be investigated further to highlight whether school size and location impacts upon quality of movement. This study employed novel accelerometer signal analytics i.e. spectral purity derived movement quality, however, there are additional approaches that could be employed, i.e. direct observational tools, this should be incorporated into future research. Thereby further refining the assessment of movement quality, in-field. The assessment of self-reported health and fitness used in this study, although not validated in combination, has been shown to be independently accurate and valid in children [300-302].

7.6 Conclusion

The first aim of this study was to characterise children's recess physical activity. This investigation found that overall recess activity (integrated acceleration) was invariant day-to-day, however the underlying frequency and harmonic component (spectral purity) derived movement quality was significantly different between days. The second aim of this study was to investigate how frequency spectrum movement quality characteristics cluster during school recess. It was found that overall activity and frequency and harmonic content of ambulatory movement cluster during uncontrolled physical activity. In addition, frequency and harmonic content was more closely linked to self-perceptions of health and fitness than overall activity. The analysis of frequency and harmonic content of movement quality, in conjunction with overall activity is demonstrably sensitive and informative in characterising children's recess physical activity. This has important practical implications, particularly related to intervention monitoring and assessing human movement. Researchers should consider using frequency spectrum derived quality and quantity of movement to assess physical activity interventions, at a group and individual level. Further research should seek to better quantify and qualify physical activity in contextualised settings to enhance our understanding of specific movement and ambulation patterns, with emphasis on development through the ages and the utility of novel analytics in early years' children.

7.7 Summary: Experimental Chapter Three

The aims of this experimental chapter were to characterise children's recess physical activity, and investigate how movement quality characteristics of gait cluster during school recess

Accordingly, there were no significant inter-day differences found for overall activity (P>0.05), yet significant differences were found for spectral purity (P<0.001). Integrated acceleration was clustered with spectral purity, in addition to significant positive correlation coefficients between integrated acceleration and spectral purity (P<0.05), whilst BMI percentile was negatively correlated with integrated acceleration and spectral purity.

Overall, this was the first empirical study to report spectral purity of children's gait in an uncontrolled setting and demonstrated that the spectral purity of children's movement is variable day-to-day, whereas overall activity is not.

The final experimental chapter in this thesis will further seek to analyse and characterise movement quality characteristics in children during un-controlled activity, i.e. free-play, in addition to assessing motor competency.

Thesis map

Chapter	Study		Outcomes
1	SlamTracker Accuracy under Static and Controlled Movement Conditions	*Aim*	To quantify the mean, standard deviation and variance of the SlamTracker device at a range of speeds
		Key Findings	Sample variance was <0.001g across all speeds and axes during the movement condition tests. In conclusion, the SlamTracker is shown to be an accurate and reliable device for measuring the raw accelerations of movement.
	Validity of Force and Angle Derivation Using Raw Accelerometry	*Aim*	To verify the validity of using raw accelerometry to estimate force (N) and leg angle (°) during ambulation.
		Key Findings	Angle estimation (°) and force derivation (N), using an accelerometer, significantly correlated with video verified angle estimation (r=0.98, p=0.001) and force platform verified values (r=0.98, p=0.001), respectively.
	A Kinematic Analysis of Fundamental Movement Skills	*Aim*	To characterise the relationship between facets of fundamental movement and, to characterise the relationship between overall integrated acceleration and three-dimensional kinematic variables whilst performing fundamental movement skills.
		Key Findings	Overall integrated acceleration was comparable between participants (CV: 10.5), whereas three-dimensional variables varied by up to 65%. Indicating that although overall activity may be correspondent, the characteristics of a child's movement may be highly varied.
2	Profiling Movement Quality and Gait Characteristics According to Body-Mass Index in Children (9-11y)	*Aim*	To apply automated, novel analyses to characterise the movement quality of children during the multi-stage fitness test, and to report how movement quality characteristics of gait cluster according to BMI
		Key Findings	OB children had significantly lower spectral purity and time to exhaustion (TTE) than UW NW, and OW children (P<0.05). BMI was clustered with stride profile, and TTE with spectral purity. Significant negative correlation (P<0.05) between BMI and; TTE (r=-0.25), spectral purity (r=-0.24), integrated acceleration (r=-0.22), stride angle (r=-0.23) and stride variability (r=-0.22). Spectral purity was representative of children's performance during the MSFT.
3	Profiling Movement Quality and Gait Characteristics of Recess Activity in 9-11-year-old Primary School Children	*Aim*	To characterise children's recess physical activity, and investigate how movement quality characteristics of gait cluster during school recess
		Key Findings	There were no significant inter-day differences found for overall activity (P>0.05), significant differences were found for spectral purity (P<0.001). Integrated acceleration was clustered with spectral purity. There were significant positive correlations coefficients between integrated acceleration and spectral purity (P<0.05), whilst BMI percentile was negatively correlated with integrated acceleration and spectral purity.
4	Profiling Movement and Gait Characteristics in Early-Years Children (3-5y)	*Aim*	To characterise children's free-play physical activity and investigate how movement quality characteristics of gait cluster in children (3-5y).
		Key Findings	-

8.0 Experimental Chapter 4

8.1 Profiling Movement and Gait Characteristics in Early-Years Children (3-5y).

*this chapter is a submitted manuscript: Clark, C. C. T., Barnes, C. M., Swindell, N. J., Bingham, D. D., Collings, P. J., Barber, S. E., Holton, M. D., Summers, H. D., Mackintosh, K.A., Stratton, G. (2016). Profiling movement and gait characteristics in early-years children (3-5y). Submitted to *Journal of Motor Behaviour*, February 2017.

8.2 Introduction

Global physical activity guidelines recommend that early years children (3-5 years) engage in at least 180 minutes of physical activity every day (Department of Health [65], Department of Health and Aging [66], Tremblay, et al. [67]). Demographic, biological, sociocultural, and motor competence can all impact upon physical activity levels [24,92,313]. Specifically, Stodden, et al. [22] highlighted an interaction between motor competence, perceived motor competence, cardiorespiratory fitness and physical activity levels. Further, recent prospective studies have established that development of motor competence has numerous tangible health and developmental benefits. For example, higher levels of motor competence are shown to positively predict cardiorespiratory fitness [314], improved academic performance [315], and are protective against overweight and obesity [316]. Concerningly, studies have reported low levels of competence among primary school aged children [317,318]. These findings highlight the need to examine motor competence during early years (3-5 years), which is considered a critical phase for fundamental movement skill development [319]. During this period, neuromuscular maturation and rapid cognitive development affect motor skill acquisition and development [320]. Motor development during the early years is considered a facilitator for lifelong physically active lifestyles, and children's perceptions of their competency is asserted to influence this development [318]. For example, older children who perceive themselves as having poor motor competence may fall into a negative spiral of disengagement, further limiting motor development, physical activity and cardiorespiratory fitness [22]. Several studies have documented low levels of motor competence among early years' children [99,321-325]. Motor competence in the early years is traditionally assessed using observation tools in a controlled setting, such as the movement assessment battery for children (MABC2 [87]) or the test of gross motor development (TGMD [324,326]). To our knowledge there have been no objective measurements of motor competence and movement quality during habitual child activity [32], and this dearth of literature has resulted in limited insight into children's motor development. We postulate that objective measures and novel analytics will provide insight into the quality and quantity of movement in parallel [32].

Developments in the field of objectively measured physical activity are moving with expediency [32]. For example, accelerometers can be used to characterise gait patterns and determine safety, control, balance, variability and rhythmicity during ambulation [18,19,194,259,260]. These characteristics are retrievable using the frequency and harmonic content of the accelerometer signal, and used to examine the symmetry within a movement by exploiting the periodicity of the signal [295,296].

Raw acceleration signals, that have not undergone proprietary pre-processing, can be analyzed in the frequency domain using Fourier analysis to assess gait and movement in-field and to profile movement quality in children, respectively [18,218,297]. However, this has not been applied in early years' children's activity in natural settings, such as free-play. Statistically, the use of traditional measures to study physical activity in humans assumes that variations are random and independent of past and future repetitions [281], contrastingly however, it has been shown that such variations are distinguishable from noise and warrant further investigation [44,282-285]. Moreover, frequency spectrum characteristics derived from an accelerometer signal are significantly related to movement quality, cardiorespiratory fitness, running strategy and body mass index in primary school children (Clark, et al. [218] and Barnes, et al. [299]).

Numerous and complex characteristics of movement and lifestyle in adults and children (9-11y) can be reliably analysed using cluster analysis [47,215,218]. Hierarchical clustering is an analytic procedure that reduces multi-factorial data into smaller subsets. Clustering yields groupings that are based on the similarity of whole cases, as opposed to the individual variables that comprise those cases [45]. Cluster analysis has been used to profile and classify systems or taxonomies [45,46], and whilst it has consistently been applied in other disciplines, such as nanotechnology and cell biology [327-331], it has only recently been used successfully to investigate human movement characteristics [218].

Although some recent work has examined the relationship between motor skills and physical activity, in a standardised setting (incorporating accelerometry) [262,263], there has been no attempt in the literature to use clustering algorithms to profile and compare derivatives of a raw acceleration trace (spectral purity, integrated acceleration) during free-play in early years' children. There is clearly potential to derive more information from the signal output of accelerometers [32]. Therefore, the aims of this study were two-fold; to characterise children's free-play physical activity and investigate how movement quality characteristics of gait cluster in children (3-5y).

8.3 Method

8.3.1 Participants and Settings

Sixty-one children (39 boys, 4.3±0.7y, 1.04±0.05m, 17.8±3.2kg, body mass index; 16.2±1.9 $kg{\cdot}m^2$) volunteered to take part in this study from two primary schools in Northern England, U. K (77% South Asian, 11% White British, 11% Other/Mixed). Prior to research commencing, informed parental consent and child assent was attained. This study was ethically approved and adhered to the institutional ethical guidelines.

8.3.2 Instruments and Procedures

Children took part in a free-play period (104 ± 12 minutes per day) while their physical activity was recorded using a custom-built Micro Electro-Mechanical System (MEMS) based device, which incorporated a tri-axial accelerometer with a +/- 16g dynamic range, 3.9mg point resolution and a 13-bit resolution (with a z-axis amplitude coefficient of variation of 0.004% at 40 Hz [230];ADXL345 sensor, Analog Devices). The MEMS device was housed in a small plastic case and affixed via a Velcro strap to the lateral malleolar prominence of the fibula of the right leg and set to record at 40 Hz [218,299]. Activity was also measured using an additional ActiGraph GT3X+ device (ActiGraph, Pensacola, FL, USA) mounted on the right hip and set to record at 100 Hz. All children also completed the movement assessment battery for children, second edition, using standardised procedures (MABC2; as detailed in: Henderson, et al. [87]).

Anthropometrics

Stature (measured to the nearest 0.01m) and body mass (to the nearest 0.1kg) were measured using standard procedures using a stadiometer and digital scales (SECA, Hamburg, Germany), respectively [212]. Skinfold measurements were made by the same observer using a skinfold calliper (Harpenden, Baty International, U.K.) following standard procedures described by Lohmann, et al. [212] . Measurements were made at the triceps and subscapular sites, in addition to waist circumference, which provides a valid estimate of body fat percentage [332] (Eisenmann, et al. [333]). Further, children were classified as either underweight (≤5th percentile), normal weight (5th to 85th percentile), overweight (>85th to <95th percentile) or obese (≥ 95th percentile) [213].

8.3.3 Data Analysis

Raw acceleration data were uploaded into MatLab (MATLAB version R2016a), where integrated acceleration and spectral purity were derived [218,299]. The characteristics used for analysis were derived from acceleration in the axis along the lower leg towards the origin of motion, termed the radial axis. The integrated acceleration was determined using an integration of the rectified raw acceleration signal [214]. ActiGraph acceleration data were analyzed using a commercially available analysis tool (KineSoft version 3.3.67, KineSoft; www.kinesoft.org). Non-wear periods were defined as any sequence of >20 consecutive minutes of zero activity counts [334]. Sedentary behaviour was defined as <100 counts per minute, while 100, 2296 and 4012 counts per minute were thresholds to define light, moderate and vigorous physical activity, respectively [335,336]. Mean counts per minute during valid wear time and percentage of total time spent in moderate-to-vigorous physical activity (MVPA) were used to define total physical activity.

Spectral purity was calculated from the cumulative distribution function (CDF) of the frequency spectrum and is the gradient of the CDF at high frequency. Spectral purity measures how tightly the frequency components of the gait cycle are distributed using fundamental frequency to harmonics [218]. This frequency spectrum analysis is directly related to the gait of a participant [218,299]. A participant could have high spectral purity and low overall activity, which indicates that cyclical, high periodicity movement has occurred, however in combination with low integrated acceleration this equates to the participant remaining static, for example, sat down in one location for prolonged periods.

The MABC2 was scored by two trained, experienced assessors (reliability: r=0.96) and scores were converted into gross motor, fine motor and overall percentile scores, and subsequently described in a traffic light classification system including a red zone (1), amber zone (2), and green zone (3), following standard procedures [87]. A score below the 5th percentile was classified in the red zone indicating a significant movement difficulty, a percentile score between the 5th and 15th was classified in the amber zone indicating at risk of movement difficulty, and a percentile score >15th was classified in the green zone indicating no movement difficulty detected [87].

Cluster analysis

The derived characteristics (integrated acceleration, spectral purity, overall activity counts, MVPA percentage, BMI percentile, MABC2 classification, body fat percentage) were normalised so that they could be compared and input into an in-built clustering algorithm (MATLAB version R2016a). This algorithm goes through multiple iterative processes in order to cluster the data along the columns of the dataset. The similarity or dissimilarity between metrics was determined by calculating the pairwise Euclidean distances between the values of the different metrics.

$$d_{2st} = (x_s - x_t)(x_s - x_t)'$$

Equation 10. Euclidean distance

Where, d is the Euclidean distance; x_s and x_t represent the data values being compared.

Once the distances between the characteristics (integrated acceleration, spectral purity, overall activity counts, MVPA percentage, BMI percentile, MABC2 classification, body fat percentage) for each child were derived, a linkage function was applied, to determine the proximity of the metrics to each other. These were paired into binary clusters, which were subsequently grouped into larger clusters until a hierarchical tree was formed. The resulting clustergram was displayed in terms of a heat map and dendrogram. The height of the link at which two observations on the dendrogram were joined was analysed using cophenetic distance, to demonstrate the similarity between two clusters [46,215,216]. The values for the dendrogram linkages were subsequently normalised. The cophenetic distance ratio for the overall clustergram was also measured to demonstrate how successfully the dendrogram preserved the pairwise distances between the original unmodeled data points (where 1 is maximum).

A Shapiro-Wilk test determined that data were not normally distributed (P<0.001) and therefore non-parametric inferential methods were used for analysis. Descriptive data were presented as mean, median and upper and lower quartiles [218]. The Kruskall-Wallis test was used to determine differences between motor competence traffic light groups and post-hoc Mann-Whitney U tests, with continuity correction and tie adjustment [266], to determine specific differences between groups. Spearman's rho was used to calculate correlation coefficients between each characteristic. All inferential statistics were performed using MatLab (MATLAB version R2016a). Statistical significance was accepted at P≤0.05.

8.4 Results

Significant differences were found between MABC2 classification groups for spectral purity and integrated acceleration. Post-hoc testing found significant differences between green, amber and red MABC2 classifications for spectral purity and integrated acceleration (*P*<0.001). Descriptive data for movement and physical activity characteristics are detailed in Table 1. Significant (*P*≤0.05) relationships were found between MABC2 classification and percentage of time spent in moderate-to-vigorous physical activity (r=0.29), integrated acceleration (r=0.66) and spectral purity (r=0.7). Significant relationships were also found between spectral purity and integrated acceleration (r=0.57), and body fat percentage and BMI percentile (r=0.75). Figure 1 illustrates that integrated acceleration and spectral purity (cophenetic distance (CD): 0.19), integrated acceleration and MABC2 classification (CD: 0.19), spectral purity and MABC2 classification (CD: 0.06), were clustered together (Figure 16), with a cophenetic distance ratio for the overall clustergram of 0.95.

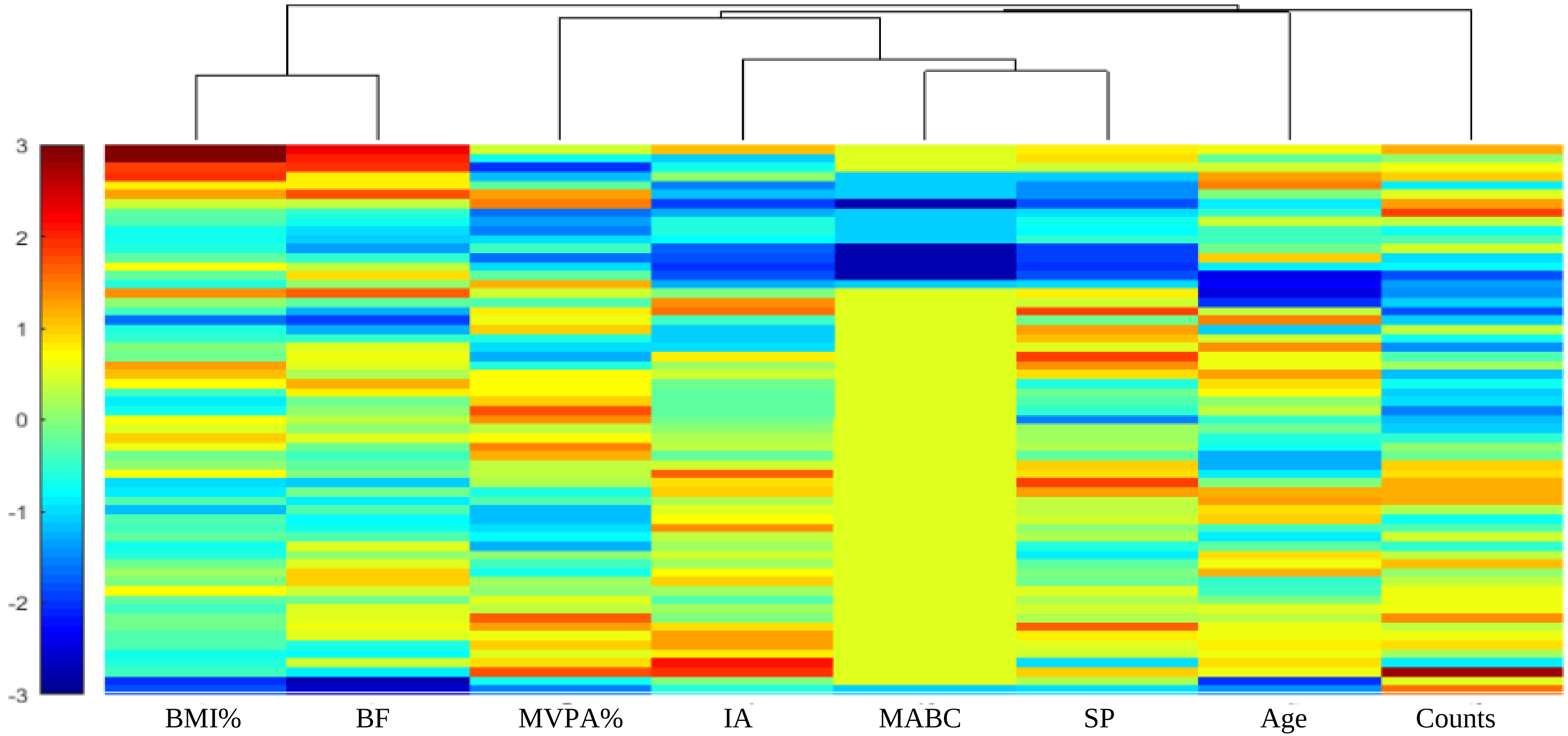

Figure 16. Clustergram and Dendrogram

Colours represent z-scores in the Clustergram. The Dendrogram highlights linkage between two or more characteristics. BMI%: body-mass index percentile, BF: body fat percentage estimation, MVPA%: percentage of time spent in moderate-to-vigorous physical activity, IA: integrated acceleration, MABC: movement ABC classification, SP: spectral purity, Counts: accelerometer counts.

8.5 Discussion

The aims of this study were to characterise children's free-play physical activity, and investigate how movement quality characteristics of gait cluster in children (3-5y).

8.5.1 Clustergram overview

In order for a clustergram to be considered statistically accurate, a cophenetic distance ratio of 0.75 is required [303]. The clustergram in this study had a cophenetic distance ratio of 0.95, indicating confidence in the veracity of clusters identified. The clustering algorithm hierarchically linked each characteristic (integrated acceleration, spectral purity, overall activity counts, MVPA percentage, BMI percentile, MABC2 classification, body fat percentage), accordingly. The proximity of two or more characteristics within the clustergram indicated how closely the movement quality characteristics were linked to each other [46,215], for example, MABC2 classification and spectral purity: 0.06, integrated acceleration and spectral purity: 0.19. The cophenetic distance ratio reported in the present study indicates that movement characteristics were successfully, and reliably, clustered. Hierarchically clustering movement characteristics has previously been shown to be successful in pre-adolescent children and close cophenetic distances between spectral purity and aerobic performance were highlighted [218]. However, this is the first study to utilise and report the hierarchical clustering of movement characteristics in early-years children.

8.5.2 Integrated acceleration, spectral purity and motor competence

The frequency and harmonic content of movement is reflective of movement characteristics such as gait pattern, overall physical activity and cardiorespiratory fitness [218,337]. In this study, spectral purity and motor competence (MABC2 classification) were more closely cophenetically linked (0.06) than integrated acceleration (0.19), which was previously unreported. Furthermore, traditional correlation analyses found spectral purity (r=0.7) and integrated acceleration (0.66) were significantly correlated with motor competence. These findings suggest that spectral purity and integrated acceleration may be movement quality indicators in early years' children, congruent with previous findings where spectral purity was demonstrated to be indicative of fundamental aspects of movement in pre-adolescent children (9-11y) [218]. Furthermore, in a population of geriatric and Parkinsonian sufferers', accelerometer signals in the frequency domain reveal deteriorating gait characteristics and assess fall potential, respectively [20,21]. To the authors' knowledge, the present study is the first to demonstrate that spectral purity and motor competence are related in early years' children (Figure 16).

Integrated acceleration, a proxy measure for overall physical activity [34,218], was positively related to motor competence in the present study and this is supported widely in the literature [24,31,93,321]. Although some studies have relied upon self-report proxies of physical activity [238,239], a recent review found a positive relationship between motor competence and health-related benefits [24]. Further, Holfelder, et al. [94] and Lubans, et al. [92] also reported positive associations in respective systematic reviews, and Cohen, et al. [240] demonstrated that overall physical activity was positively correlated with locomotor and object control competency. Congruent with previous work [92,94,240], integrated acceleration was significantly different by MABC2 classification ($P<0.001$). However, spectral purity was also found to significantly different by MABC2 classification ($P<0.001$). In preceding work, empirical evidence suggested that spectral purity was a viable proxy measure of the fundamental aspects of movement and that it clustered with motor competence (see: Clark, et al. [218] and Barnes, et al. [299]). Further, given that the present study has demonstrated that spectral purity is clustered with movement competence and significantly different between motor competency classification, suggests underlying frequency components of movement should be further investigated for the measurement of movement quality in children [218]. Moreover, whilst it has been demonstrated that a proxy for overall physical activity was positively correlated with motor competence [92,94,240], spectral purity (r=0.7) was found to have a stronger relationship to motor competence than overall activity (r=0.66) in the present study, thereby highlighting the need for future research to examine and further establish this relationship.

8.5.3 Anthropometrics. age and actigraphy

Congruent with previous research, the present study found that BMI and body fat percentage were closely cophenetically clustered and significantly positively correlated [338,339]. Whilst previous research has highlighted that motor competence and physical activity are inversely correlated with weight status in children [100-103], this study found that anthropometric characteristics were not clustered, nor correlated to any other measure (Figure 16). This is reflected in the literature, as Ekelund, et al. [340] and Vorwerg, et al. [341] reported no differences in physical activity levels in early years' children according to BMI and that physical activity levels did not significantly differ between overweight/obese children and normal-weight peers, respectively. Further, Williams, et al. [342] reported that there was no significant association between BMI and motor skill performance concluding that whilst weight status of early years' children was considerably influenced by socioeconomic status, physical activity levels were not, potentially due to the highly transitory and frequent movement during nursery/preschool.

Traditional hip-mounted accelerometer data did not cluster with any movement characteristic, whilst concurrent ankle-mounted raw accelerometry yielded significant results. One explanation is that traditional hip-mounted accelerometers have inadequate band-pass filtering, where high frequency movement and noise information can escape the filter adding unexplained variation in activity counts [35]. Further, Wundersitz, et al. [228] identified that filters with at least an 8 or 10 Hz cut-off frequency were most suitable to process accelerations in ambulatory tasks, and thus adopted in the present study, whereas the actigraphy device utilised filters out frequencies higher than 2.5 Hz [35,228]. This finding highlights the insensitivity of traditional, hip-worn actigraphy units to measure contextualised physical activity. Physical activity is a multi-directional, complex construct and summative activity counts are a measure of centrality that are missing vital information [44,122]. This study highlighted that integrated acceleration and spectral purity are hierarchically clustered and significantly correlated with motor competency, whereas traditional, hip mounted, physical activity measures do not.

8.5.4 Limitations

The clustering algorithm utilised within this study was structured using hierarchical methods, thereby pairing characteristics according to proximity. This means inverse relationships may be difficult to ascertain. However, this can be mitigated with careful interpretation of the clustergram, in addition to incorporating other correlation analyses (i.e. Spearman's rho). Although this study employed novel signal analytics of accelerometer data, it only assessed spectral purity and integrated acceleration, and therefore further analytics could be employed and should be the focus of future research.

8.6 Conclusion

The aims of this study were to characterise children's free-play physical activity and to investigate how movement characteristics of gait cluster in children (3-5y). Overall, integrated acceleration and spectral purity were significantly different between motor competence classifications. Further, that overall physical activity and spectral purity cluster during uncontrolled free-play physical activity, whilst spectral purity was more closely linked to motor competence than integrated acceleration. Anthropometric and actigraphy characteristics were not correlated to, or clustered meaningfully with, any other measure.

This study has built upon previous research [218,299,304] suggesting cophenetic clustering of spectral purity with integrated physical activity and motor competence, and has attempted to address the dearth of suitable metrics available to quantify movement quality. The analysis of frequency and harmonic content of movement and overall physical activity concomitantly is demonstrably sensitive and informative. It is recommended that future research seeks to better quantify and qualify physical activity in contextualised settings to enhance our understanding of specific movement and gait patterns. Furthermore, the link between spectral purity and motor competence highlighted in this study necessitates detailed further investigation.

8.7 Summary: Experimental Chapter Four

The aims of this experimental chapter were two-fold; to characterise children's free-play physical activity and investigate how movement quality characteristics of gait cluster in children (3-5y). Accordingly, significant differences were found between motor competency classifications for spectral purity and integrated acceleration (P<0.001). Spectral purity was hierarchically clustered with motor competence and integrated acceleration. Significant positive correlations were found between spectral purity, integrated acceleration and motor competence (P<0.001). Metrics capable of objectively quantifying movement quality in children are evidently missing. Furthermore, although objective movement quality characteristics have been investigated in pre-adolescent children, they have not been investigated in early years' children. This was the first empirical investigation to report spectral purity in early years' children and results demonstrate that the underlying frequency component of movement is clustered with motor competence.

Thesis map

Chapter	Study		Outcomes
1	SlamTracker Accuracy under Static and Controlled Movement Conditions	*Aim*	To quantify the mean, standard deviation and variance of the SlamTracker device at a range of speeds
		Key Findings	Sample variance was <0.001g across all speeds and axes during the movement condition tests. In conclusion, the SlamTracker is shown to be an accurate and reliable device for measuring the raw accelerations of movement.
	Validity of Force and Angle Derivation Using Raw Accelerometry	*Aim*	To verify the validity of using raw accelerometry to estimate force (N) and leg angle (°) during ambulation.
		Key Findings	Angle estimation (°) and force derivation (N), using an accelerometer, significantly correlated with video verified angle estimation (r=0.98, p=0.001) and force platform verified values (r=0.98, p=0.001), respectively.
	A Kinematic Analysis of Fundamental Movement Skills	*Aim*	To characterise the relationship between facets of fundamental movement and, to characterise the relationship between overall integrated acceleration and three-dimensional kinematic variables whilst performing fundamental movement skills.
		Key Findings	Overall integrated acceleration was comparable between participants (CV: 10.5), whereas three-dimensional variables varied by up to 65%. Indicating that although overall activity may be correspondent, the characteristics of a child's movement may be highly varied.
2	Profiling Movement Quality and Gait Characteristics According to	*Aim*	To apply automated, novel analyses to characterise the movement quality of children during the multi-stage fitness test, and to report how movement quality characteristics of gait cluster according to BMI

	BMI in Children (9-11y)	*Key Findings*	OB children had significantly lower spectral purity and time to exhaustion (TTE) than UW NW, and OW children (*P*<0.05). BMI was clustered with stride profile, and TTE with spectral purity. Significant negative correlation (*P*<0.05) between BMI and; TTE (r=-0.25), spectral purity (r=-0.24), integrated acceleration (r=-0.22), stride angle (r=-0.23) and stride variability (r=-0.22). Spectral purity was representative of children's performance during the MSFT.
3	Profiling Movement Quality and Gait Characteristics of Recess Activity in 9-11-year-old Primary School Children	*Aim*	To characterise children's recess physical activity, and investigate how movement quality characteristics of gait cluster during school recess
		Key Findings	There were no significant inter-day differences found for overall activity (*P*>0.05), significant differences were found for spectral purity (*P*<0.001). Integrated acceleration was clustered with spectral purity. There were significant positive correlations coefficients between integrated acceleration and spectral purity (*P*<0.05), whilst BMI percentile was negatively correlated with IA and spectral purity.
4	Profiling Movement and Gait Characteristics in Early-Years Children (3-5y)	*Aim*	To characterise children's free-play physical activity and investigate how movement quality characteristics of gait cluster in children (3-5y).
		Key Findings	Significant differences were found between motor competency classifications for spectral purity and integrated acceleration (*P*<0.001). Spectral purity was hierarchically clustered with motor competence and integrated acceleration. Significant positive correlations were found between spectral purity, integrated acceleration and motor competence (*P*<0.001)

9.0 Thesis Synthesis

The overarching aim of this thesis was to characterise and profile children's physical activity movement and gait quality. The overarching aim was achieved through a series of experimental chapters, each with specific aims and findings, outlined in the thesis map.

The challenge this thesis sought to address was based upon the premise that: i) there are numerous, acute physiological and psychosocial benefits to physical activity among children and adolescents; ii) physical activity behaviours between childhood and adulthood are correlated and; iii) physically active children are more likely to grow up to be physically active and healthy adults [15,16]. It has therefore been commonplace to quantify energy expenditure in children, both cross-sectionally and longitudinally [10,15-17]. However, there is a paucity of research demonstrating objective methods to empirically derive movement quality, or integrate physical activity quantities and qualities. Quality is an ambiguous term, with varying meanings relating to; psychology, physiology, biochemistry, well-being, emotional state, biomechanics or even life. However, throughout this thesis the term 'quality' was defined as, and derived from, the purity of the fundamental frequency spectra (signal) during human movement, specifically relating to gait.

The novelty of this thesis encompasses numerous analytical techniques, such as; hierarchical clustering, frequency domain analysis and spectral purity. The challenges that needed to be addressed during this thesis involved ensuring that, i) we could introduce an informative, representative and robust measure of movement and gait quality, and, ii) to suitably characterise children's movement and gait quality in controlled and uncontrolled settings. These challenges were initially met through a battery of smaller studies (experimental chapter 1), which led to the conception of the subsequent experimental chapters, each building upon the previous chapter.

Following numerous laboratory-based studies, testing the specification and application of the SlamTracker device, confidence was asserted that the device was valid and reliable for the in the field approach being utilised in the experimental work. Experimental chapter 1 encompassed a body of work that sought to understand the utility raw accelerometry had in mechanical, controlled and semi-controlled movements. This work confirmed that, in a mechanical setting, a raw accelerometer is robust and accurate at a range of controlled speeds. Further, this chapter demonstrated that temporal movement variables, force estimation and leg-lift angle, can be accurately computed from a single, ankle mounted accelerometer. The final tenet of the first experimental chapter formed a large basis for the continued work in the subsequent chapters (i.e. the finding that during standardised fundamental movements, although overall physical activity may be invariable, individual movement characteristics display large temporal and kinematic flux).

The overarching aim of this thesis necessitated novel analytics being accurate and easy to perform. In accord with this aim, the computational accuracy of force and angle estimation from the SlamTracker device were affirmed. This was a significant stage in the thesis, and demonstrated that the SlamTracker could be utilised to accurately compute key variables in children's movement, both of which would be integral to more complex and novel analytics. The final study in experimental chapter 1 facilitated establishing the niche in the literature this thesis could fill. In standardised, fundamental movements, traditional measures of overall activity showed minimal variance. Whereas detailed kinematic variables highlighted the significant differences between children. Therefore, experimental chapter 2 sought to explore the application of raw accelerometry and employ novel analytics to investigate movement quality characteristics. The aims of the second experimental chapter 2 were to characterise the movement quality of children during a standardised fitness test, and report how derived movement quality characteristics of gait cluster according to weight status. This experimental chapter was necessary for establishing a credible base for the combination of raw accelerometry and novel analytics and was the first empirical study to draw upon frequency domain analysis and hierarchical clustering in the characterisation of movement in children. This study elucidated that traditional and novel performance characteristics during a standardised fitness test differed between body mass indices, and were significantly negatively correlated with body mass indices. One of the principal findings of this study was that spectral purity hierarchically clustered with time to exhaustion (the key performance indicator in the fitness test).

This second experimental chapter provided empirical evidence that novel analytics, supported by the systematic review undertaken within this body of work, are robust and informative, offering new insights into children's movement quality. Experimental chapter 1 and 2 both utilised more controlled, standardised movements and given the success in both chapters', experimental chapter 3 moved away from controlled into more free-form, uncontrolled settings, i.e. recess. This was an important step to take as this would demonstrate the robustness of the novel analytics in less controlled environments.

Congruent with experimental chapter 1, experimental chapter 3 found that overall physical activity remained invariant between children. Upon examining overall physical activity across numerous days, there were no significant inter-day differences found. On the other hand, significant inter-day differences in spectral purity were highlighted. Further, overall physical activity (measured by integrating accelerations) was hierarchically clustered with spectral purity, in addition to significant positive correlation coefficients between activity and spectral purity ($P<0.05$). Additionally, in congruence with experimental chapter 2, body mass indices were negatively correlated with activity and spectral purity.

The third experimental chapter highlighted that the novel analytics utilised in this thesis were stable and robust in a volatile environment (i.e. recess). Demonstrating that, although overall physical activity is invariant, spectral purity can significantly differ daily. This was an important finding to empirically evidence, however raised the question, can we characterise children's movement quality from an early age, using a stable, robust measure? The rationale for moving into early years aged children was based upon; i) the link established between spectral purity and movement quality, ii) the tenuous literature on motor competency development through childhood, and, iii) the evidence motor competence may track though the life course. Therefore, it was deemed prudent to examine fundamental frequency characteristics in early years' children, in conjunction with traditional motor competency assessment.

The final experimental chapter sought to follow on from the experimental chapter 3 and characterise children's free-play physical activity and, investigate how movement quality characteristics of gait cluster with free-play and motor competence in early years' children (3-5y). Accordingly, significant differences were found between motor competency classifications for spectral purity and overall physical activity (*P*<0.001). Spectral purity was hierarchically clustered with motor competence and overall physical activity. Furthermore, significant positive correlations were found between spectral purity overall physical activity and motor competence (*P*<0.001).

Overall, this body of work was able to successfully profile and characterise children's movement and gait quality in a variety of scenarios, from controlled, laboratory-based settings to un-controlled free-play. The novel quality measure coined in this thesis, spectral purity, was shown to be hierarchically clustered with, and indicative of, performance, physical activity and motor competence. This thesis has expanded the current evidence base on children's physical activity and movement and demonstrated that raw accelerometry can be used, in conjunction with novel analytics, to provide innovation in movement quality assessment across ages. Future research should seek to measure and track movement quality measures longitudinally, from the early years and into adulthood. In the contextualised scenarios used within the experimental chapters of this thesis, spectral purity has been a stable measure of quality, and hierarchical clustering of movement variables has enabled novel characterisation of children's movement quality. In order for these analytical techniques and novel measures to grow and become more commonplace, more background work will be required. A large cross-sectional data collection should occur in children, adolescents, adults and the elderly to create an index of movement quality during standardised tasks. Following this, a detailed investigation of how traditional health and fitness markers and novel quality indicators (spectral purity) impact risk stratification through the life course should be undertaken. Additionally, researchers who use traditional methods of assessing intervention success and viability, in the context of physical activity, health and well-being, should consider utilising movement quality markers in conjunction with overall quantity measures.

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11.0 Appendices

Appendix I

Extension to Experimental Chapter 3

Multiple linear regressions were performed on the data presented in Experimental chapter 3 to ascertain the robustness of spectral purity. Mean integrated acceleration (F (1,22) = 7.88, r^2 = 0.23), BMI (F (1,22) = 0.09, r^2 = -0.25), self-perceived health (F (1,22) = 16.02, r^2 = 0.39), self-perceived fitness (F (1,22) = 7.56, r^2 = 0.22) significantly predicted spectral purity (P<0.05). Whilst, integrated acceleration coefficient of variation (F (1,22) = 7.88, r^2 = 0.07), spectral purity coefficient of variation (F (1,22) = 0.902, r^2 = -0.04), and sex (F (1,22) = 2.47, r^2 = 0.06), did not significantly predict spectral purity (P>0.05).

The rationale for performing this further analysis was to investigate the extent to which spectral purity was influenced by other variables. For experimental chapter 3, integrated acceleration, body-mass indices, self-perceived health and self-perceived fitness were significant predictors of spectral purity. This finding is congruent with experimental chapter 2 which highlighted that spectral purity differs across body-mass indices and fitness levels and is significantly, negatively correlated. In experimental chapter 3, the strongest predictor of high spectral purity was self-perceived health (r^2=0.39). Overall, these findings suggest that activity levels, self-perceptions and anthropometrics cannot wholly predict spectral purity. This further validates spectral purity as robust measure that is not an artefact of other variables.

Extension to Experimental Chapter 4

Multiple linear regressions were performed on the data presented in Experimental chapter 4 to ascertain the robustness of spectral purity. Movement-ABC classification (F (1,59) = 75.6, r^2 = 0.55), and integrated acceleration (F (1,59) = 34.6, r^2 = 0.36) significantly predicted spectral purity (P<0.05). Whilst, age (F (1,59) = 1.39, r^2 = 0.006), BMI (F (1,59) = 0.22, r^2 = -0.013), body fat percentage estimation (F (1,59) = 0.003, r^2 = -0.017), Actigraph counts (F (1,59) = 1.99, r^2 = 0.016), and percentage of time spent in MVPA (F (1,59) = 0.846, r^2 = -0.003), did not significantly predict spectral purity (P>0.05).

The rationale for performing this further analysis was to investigate the extent to which spectral purity was influenced by other variables. For experimental chapter 4, movement-ABC classification and integrated acceleration were significant predictors of spectral purity. In experimental chapter 4, the strongest predictor of high spectral purity was movement-ABC classification (r^2=0.55). Overall, the finding that a measure of motor competency may account for 55% of the variance in spectral purity indicates that it (spectral purity) may be a representative of a fundamental feature of movement quality/competence. This further validates spectral purity as robust measure that is not an artefact of other variables, and, in combination with the detailed results within this thesis, indicate spectral purity should be investigated further, with particular emphasis on how this robust measure tracks across ages.

Appendix II

Submitted manuscripts

Clark, C. C. T., Barnes, C. M., Swindell, N. J., Bingham, D. D., Collings, P. J., Barber, S. E., Summers, H. D., Holton, M. D., Mackintosh, K. A., Stratton, G. Profiling movement and gait characteristics in early-years children (3-5y). Submitted to *Journal of Motor Behaviour* in February 2017.

Abstract

There is a dearth of suitable metrics capable of objectively quantifying movement competence. Further, objective movement quality characteristics during free-play have not been investigated in early years' children. The aims of this study were to characterise children's free-play physical activity and to investigate how gait quality characteristics cluster with free-play in children (3-5y). Sixty-one children (39 boys, 4.3±0.7y, 1.04±0.05m, 17.8±3.2kg) completed the movement assessment battery for children and took part in free-play whilst wearing an ankle- and hip-mounted accelerometer. Characteristics of movement quality were profiled using a clustering algorithm. Spearman's rho and the Mann-Whitney U tests were used to assess relationships between movement quality characteristics and motor competence classification differences in integrated acceleration and spectral purity, respectively. Significant differences were found between motor competency classifications for spectral purity and integrated acceleration (P<0.001). Spectral purity was hierarchically clustered with motor competence and integrated acceleration. Significant positive correlations were found between spectral purity, integrated acceleration and motor competence (P<0.001). This is the first study to report spectral purity in early years' children and our results suggest that the underlying frequency component of movement is clustered with motor competence.

Presentations

Clark, C. C. T., Barnes, C. M., Mackintosh, K. A., Summers, H. D., Stratton, G. (2015). Quantitative, multiscale profiling of Motion and Activity in Children. 20th Annual Conference of the European College of Sport Science, Malmo, Sweden.

Clark C. C. T., Barnes, C.M. (2015). Physical activity measurement in children. Wales Exercise Medicine Symposium, Swansea, UK.

Clark, C. C. T., Barnes, C. M., Holton, M. D., Mackintosh, K. A., Summers, H. D., Stratton, G. (2016). Profiling movement quality characteristics according to body-mass index in children. 21st Annual Congress of the European College of Sport Science, Vienna, Austria.

Appendix III

Additional Methods

Multi-stage Fitness Test

Participants completed the multi-stage fitness test (MSFT) by running back and forth along a 20m course, and were required to touch the 20m line at the same time that a sound signal was emitted from a pre-recorded audio disk. The frequency of the sound emissions increased in line with running speed (detailed in Table 1). The test stopped when the participant reached volitional exhaustion and was no longer able to follow the set pace, or participants were withdrawn after receiving two verbal warnings to meet the required pace [265].

Table 11.Multi-stage fitness test section speeds and sound emissions.

Section	1	2	3	4	5	6	7	8	9	10	11	12
Running speed ($km \cdot h^{-1}$)	8.0	9.0	9.5	10.0	10.5	11.0	11.5	12.0	12.5	13.0	13.5	14.0
Sound emission (Hz)	7	8	8	9	9	10	10	11	11	11	12	12

Motion Capture

Motion capture was performed using the Vicon MX13 motion capture system (Vicon Peak, Oxford, UK), including twelve cameras sampling at 200 frames per second. For kinematic analysis, 39 retro-reflective markers of 14 mm diameter were attached to specific anatomical landmarks (Plug-In Gait Marker Set, Vicon Peak, Oxford, UK) (Figure 1) of every participant. Three-dimensional coordinates of the 39 markers were reconstructed with the Nexus software (Nexus 2.0, Vicon, Oxford, UK) and smoothed using cross validation splines [245]. Both static and dynamic calibrations were performed, and residuals of less than 2 mm from each camera were deemed acceptable.

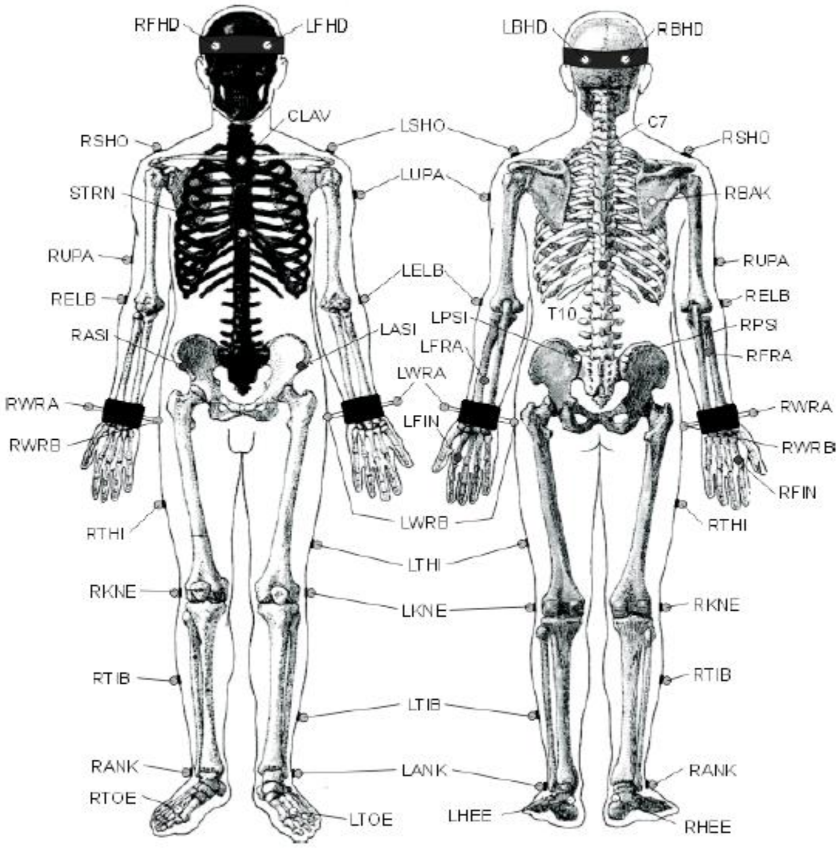

Figure 17. Vicon plug in gait markers

The 39 retro-reflective marker were placed at the following anatomical locations; the right forehead (RFHD), left forehead (LFHD), right back of head (RBHD), left back of head (LBHD), the 7th cervical vertebrae (C7), the 10th thoracic vertebrae (T10), the clavicle (CLAV), sternum (STRN), the right scapula (RBAK), the left shoulder at the acromio-clavicular joint (LSHO), the right shoulder at the acromio-clavicular joint (RSHO), the left upper arm between shoulder and elbow (LUPA), the right upper arm between shoulder and elbow (RUPA), the lateral epicondyle of the left elbow (LELB), the lateral epicondyle of the right elbow (RELB), the left forearm between the elbow and wrist (LFRA), the right forearm between the elbow and wrist (RFRA), the medial and lateral left wrist (LWRA and LWRB, respectively), the medial and lateral right wrist (RWRA and RWRB, respectively), the left hand second metacarpal head (LFIN), the right hand second metacarpal head (RFIN), the left anterior superior iliac spine (LASI), the right anterior superior iliac spine (RASI), the left posterior superior iliac spine (LPSI), the right posterior superior iliac spine (RPSI), the lateral epicondyle of the left knee (LKNE), the lateral epicondyle and the right knee (RKNE), the left thigh between the lateral epicondyle of the knee and greater trochanter (LTHI), the right thigh between the lateral epicondyle of the knee and greater trochanter (RTHI), the left lateral malleolus (LANK), the right lateral malleolus (RANK), the left tibia between the lateral epicondyle of the knee and lateral malleolus (LTIB), the right tibia between the lateral epicondyle of the knee and lateral malleolus (RTIB), the left foot second metatarsal head (LTOE), the right foot second metatarsal head (RTOE), the left heel placed on the calcaneous at the same height as the left foot second metatarsal head (LHEE), the right heel placed on the calcaneous at the same height as the right foot second metatarsal head (RHEE). Which has been used previously with a child population [246,247].

SlamTracker set-up and signal processing

Firstly, a microSD card was initialised using a command line generator, enabling the user to predefine elements such as; recording frequency, battery modifications, magnetic control, light indicators on the device, sleep and pausing of the device, number of logging hours (if required) and global positioning system interface (if externally applied) (see: Figure 18).

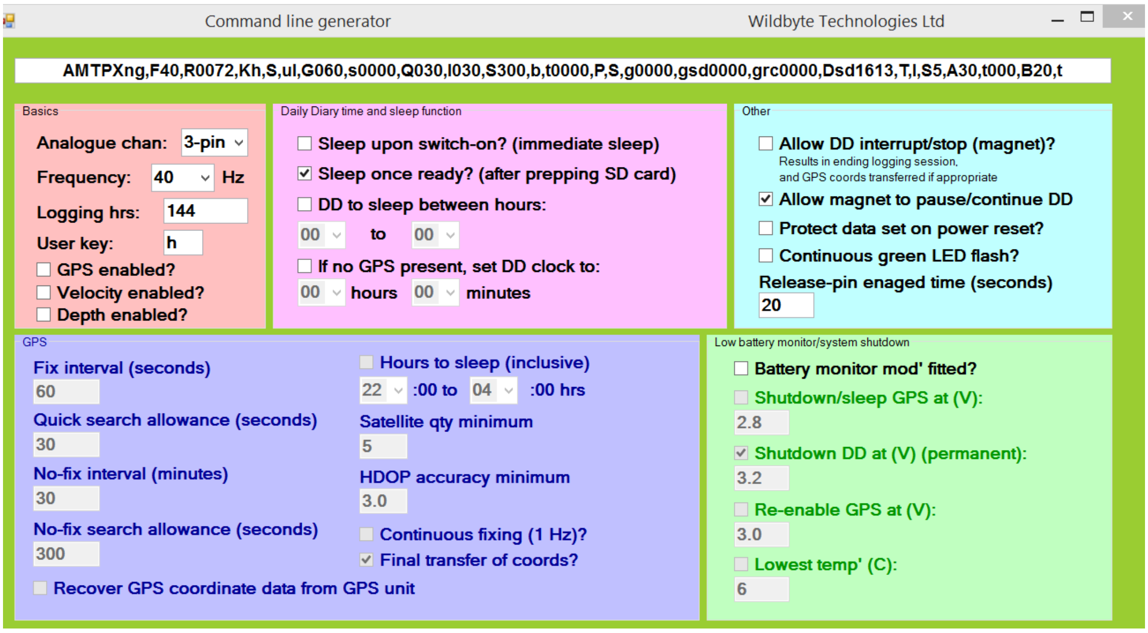

Figure 18. Command line generator for SlamTracker device

A command line is subsequently generated which controls the SlamTracker device, for example in Figure 18. "AMTPXng,F40,R0072,Kh,S,ul,G060,s0000,Q030,I030,S300,b,t0000,P,S, g0000,gsd0000, grc0000,Dsd1613,T,I,S5,A30,t000,B20,t". The generated code contains all the information on the decisions made by the researcher in the command line generator.

The SlamTracker device, in this body work, was operated via magnetic flux. As such, the device was set up in a way to enable and disable the recording function with magnetic proximity. Allowing for very specific starts, pauses and stops.

Prior to data analyses using statistical packages such as MatLab, Microsoft Excel, SPSS etc. the raw data is protected on the device in a proprietary format, preventing data loss or damage. To extract the raw signal in a usable format, i.e. text file, a data converter must be used (Figure 19). The data converter enables the user to control data input, output, split the file, display different sections of the data, adjust magnitudes and offset values, perform basic analysis (such as FFT), or simply just to convert and export in text file format.

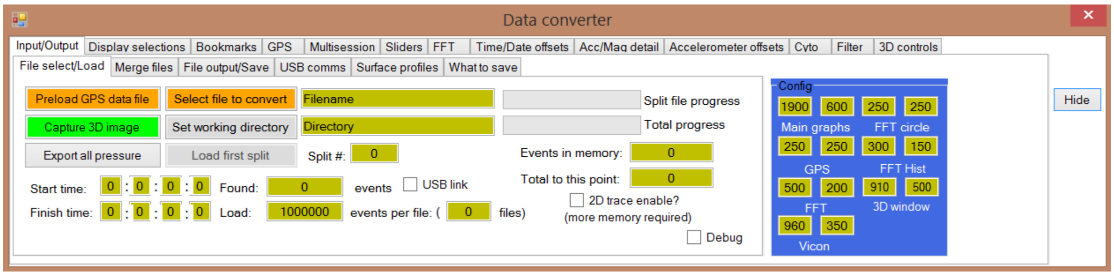

Figure 19. SlamTracker data converter

The raw trace is subsequently visualised on screen (see: Figure 20), and the user can then decide which aspects of the raw signal should be saved and converted into a text file, for example; accelerometer axes, magnetometer axes, pressure, temperature, time stamps, light level, battery level over time, in addition to derivatives of the trace such as, vector of the dynamic body acceleration (VeDBA) and overall dynamic body acceleration (ODBA).

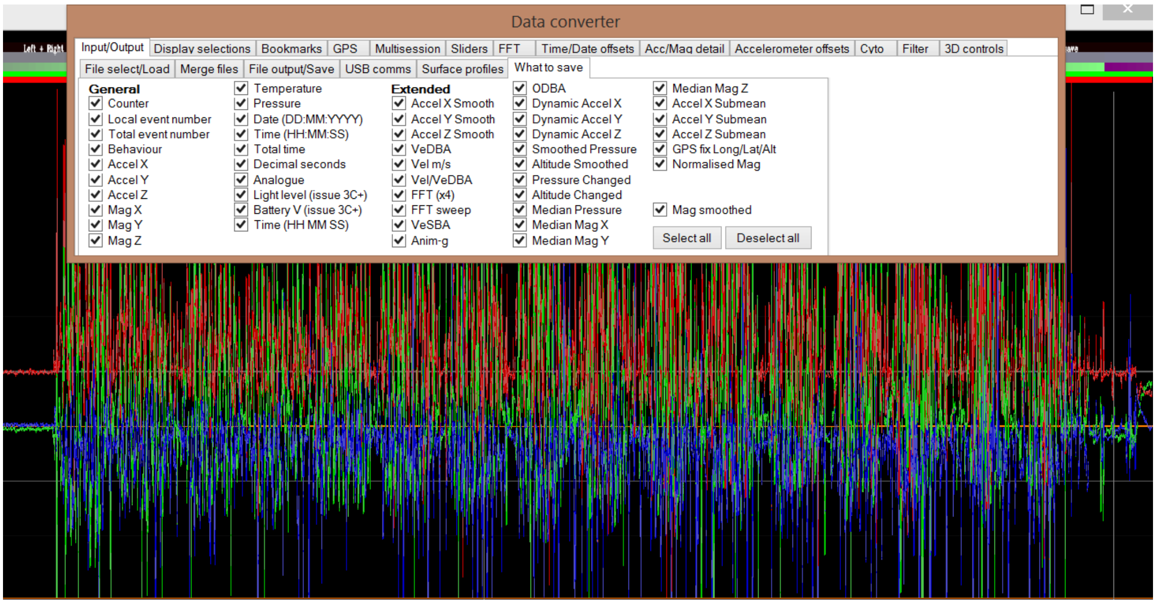

Figure 20. Data converter output decision

The data converting software then outputs all of the selected information into a text file, ready for use with programmes such as, MatLab (Figure 21).

Counter	Total Event no.	Event no.	Acc_x	Acc_y	Acc_z	Mag_x	Mag_y	Mag_z
0	14588	14588	0.827881	0.455811	0	-0.778076	0.481689	-0.16
0	14589	14589	0.827881	0.467773	0.0239258	-0.798096	0.509033	-0.16
0	14590	14590	0.803955	0.467773	0.0119629	-0.793457	0.503418	-0.17
0	14591	14591	0.803955	0.455811	0.0119629	-0.784424	0.506348	-0.16
0	14592	14592	0.86377	0.467773	0.0119629	-0.780762	0.50708	-0.16
0	14593	14593	0.827881	0.47998	0.0358887	-0.792725	0.509766	-0.16
0	14594	14594	0.851807	0.47998	0	-0.792725	0.477051	-0.16
0	14595	14595	0.839844	0.443848	0.0358887	-0.799805	0.514404	-0.16
0	14596	14596	0.839844	0.47998	0.0358887	-0.774414	0.508057	-0.16
0	14597	14597	0.815918	0.503906	0	-0.801758	0.509766	-0.17
0	14598	14598	0.803955	0.47998	0.0239258	-0.787109	0.508057	-0.16
0	14599	14599	0.815918	0.467773	0.0598145	-0.798096	0.515381	-0.16
0	14600	14600	0.791992	0.47998	0.0239258	-0.779053	0.510742	-0.16
0	14601	14601	0.815918	0.47998	0	-0.794434	0.506348	-0.16
0	14602	14602	0.815918	0.47998	0	-0.783447	0.509033	-0.16
0	14603	14603	0.815918	0.467773	0	-0.782715	0.500732	-0.17
0	14604	14604	0.827881	0.455811	0	-0.787109	0.509033	-0.16
0	14605	14605	0.839844	0.467773	0	-0.782715	0.505371	-0.16
0	14606	14606	0.86377	0.503906	-0.0239258	-0.79541	0.498047	-0.16
0	14607	14607	0.839844	0.47998	-0.0239258	-0.786133	0.509033	-0.17
0	14608	14608	0.875977	0.491943	0.0358887	-0.794434	0.482666	-0.16
0	14609	14609	0.887939	0.467773	0.0358887	-0.7854	0.48999	-0.16
0	14610	14610	0.839844	0.47998	0.0119629	-0.790771	0.502686	-0.15
0	14611	14611	0.839844	0.47998	0	-0.7771	0.510742	-0.17
0	14612	14612	0.887939	0.47998	0.0239258	-0.780762	0.509033	-0.16
0	14613	14613	0.86377	0.503906	0.0239258	-0.760742	0.512695	-0.16
0	14614	14614	0.86377	0.47998	0	-0.786133	0.506348	-0.16
0	14615	14615	0.839844	0.47998	0	-0.787109	0.498047	-0.17

Figure 21. Text file output

Skinfold (two-site assessment)

For experimental chapter 4: the skinfolds of the triceps brachii and subscapularis were measured by picking up a fold of skin and subcutaneous tissue between the thumb and forefinger, initially placed about 2 cm apart on the skin, and pinching it away from the underlying muscle (see: Tanner, et al. [343]). The width of the skinfold was measured with a calliper designed to give a constant pressure of 10 g·mm^2 over its entire opening range [344]. The instrument was held and the jaws were applied to the skinfold just under the pinch point and the right hand was allowed to relax entirely its grip on the handle so that the jaws could exert their full pressure. The left hand maintained the pinch throughout the measurement. Tanner, et al. [343] assert this results in a stable reading up to 20 mm. The dial of the calliper Holtain Skinfold Calliper) was calibrated to 0.2 mm, and the measurement was estimated to the nearest 0.1 mm, as per Tanner, et al. [343]. Skinfolds can only be measured accurately at sites where a proper fold can be raised clear of the tissues underneath. The two sites utilised in this thesis are considered suitable for assessing fat mass in children [343]. The skinfold was picked up over the posterior surface of the triceps muscle on a vertical line passing upwards from the olecranon in the axis of the limb, and the calliper jaws were applied at the marked level. The subscapular skinfold was picked up just below the angle of the left scapula with the fold either in a vertical line or slightly inclined, in the natural cleavage line of the skin. All skinfold measurements were taken by the same researcher in order to avoid any discrepancy in technique.

Accelerometer (ActiGraph GT3X)

For experimental chapter 4: this device consists of a solid-state accelerometer using an integrated micro-machined monolithic integrated circuit chip (polysilicon) to detect acceleration (Analog Devices, 2007). The GT3X makes use of a triaxial capacitive micromechanical system [345]. The sensor is suspended by springs over the surface of silicon water and provides a resistance against acceleration forces (Analog Devices, 2007). The GT3X can detect both dynamic acceleration (e.g. as a result of motion) and static acceleration (e.g. as a result of gravity forces). This GT3X incorporates an inclinometer, so may be used to detect bodily position. The GT3X accelerometer uses a 12-bit analogue-to-digital converter digitalised at 40 Hz and records acceleration in the range 0.05 to 2.0 G, making use of a band-pass filter that excludes signals outside the range 0.25 to 2.5 Hz. In experimental chapter 4, this device was housed in a small plastic case and attached via an elastic strap to the right hip of the participants, and worn for the duration of recess or free-play. Prior to data collection, the accelerometers were set up to collect data in 1-s epochs. The accelerometers were initialised using a laptop PC and were set to start collecting the data at a pre-determined time. In this way, the time on the PC was synchronised with the internal accelerometer clock.

Data analysis

Vicon

For experimental chapter 1: all corresponding data and video files were first uploaded into Vicon Nexus software and underwent in-depth analysis. Firstly, a reconstruct and labelling process was performed, allowing conversion of stereoscopic images into a three-dimensional movement. Once a three-dimensional movement had been established, a functional skeleton calibration was performed and all body segments, joint centres, bone lengths and marker movements were comprehensively modelled and trajectories were manually filtered using Woltring cross validation splines. Every single frame was scrutinised for fluidity and accuracy and marker quality was assessed. Following this, all raw data was converted into a comma separated values spread sheet for statistical analysis.

Slamtracker

Specifically investigated in experimental chapter 2, the stride profile quotient is a multi-dimensional measure derived from the mean stride frequency and mean stride angle of each child during the first and last section of running that each child completed. The absolute of the two measures between the two sections was derived and normalised. These values were then used in the following equation (equation 2), where a score of *1* would equate entirely to changes in stride frequency, and a score of *0* would equate to changes entirely in foot lift angle.

$$Q = \sin(\mathrm{atan}(D1/D2))$$

Equation 11. Stride profile quotient.

Where Q, is the stride profile quotient; sin, represents the sine function; atan, represents the inverse of the tangent; $D1$, is the = absolute difference in frequency and $D2$, is the absolute difference in foot lift angle.

Finally, time to volitional exhaustion (TTE), derived by converting events into seconds based on the sampling frequency (40 Hz) was also recorded as a measure of overall performance especially in experimental chapter 2.

Actigraph

For experimental chapter 4, following data collection non-wear periods were defined as any sequence of >20 consecutive minutes of 0 activity counts [334]. Mean counts per minute during valid wear time were used to define total physical activity. Sedentary behaviour was defined as <100 counts per minute, while 100, 2296 and 4012 counts per minute were thresholds to define light moderate and vigorous physical activity respectively [335,336]. Accelerometer data was processed using a commercially available analysis tool (KineSoft version 3.3.67, Kinesoft; www.kinesoft.org).

Appendix IV

Review of accelerometry

Accelerometers were initially used in the 1950s to measure gait velocity and acceleration [346]. Accelerometric measurement of human movement was investigated in more detail during the 1970s following device advances [347]. It was also shown that accelerometers had advantages over other techniques in quantitatively measuring human movement. With the inception of micro-electromechanical system (MEMS) technology the cost of accelerometers has reduced significantly over recent years. Furthermore, device performance has improved while the power consumption greatly reduced. The first fabricated MEMS accelerometers were reported in 1979 [348]. Since then various research and commercial applications have used MEMS accelerometers for physical activity assessment [114].

Principles of accelerometry

Accelerometers quantify acceleration using a mechanical sensing element which consists of a seismic mass attached to a mechanical suspension system with respect to a reference frame. Inertial force due to acceleration or gravity will cause the mass to deflect according to Newton's Second Law. The acceleration may then be measured electrically with the physical changes in displacement of the mass with respect to the reference frame. Piezoresistive, piezoelectric and differential capacitive accelerometers are the most commonly used accelerometers reported in the literature [349,350].

Piezoresistive accelerometers

In piezoresistive accelerometers the sensing element consists of a cantilever beam and its proof mass is formed by bulk-micromachining. The motion of the proof mass due to acceleration can be detected by piezoresistors in the cantilever beam and proof mass. The piezoresistors are arranged as a Wheatstone bridge to produce a voltage proportional to the applied acceleration [114]. Piezoresistive accelerometers are simple and low-cost. The piezoresistive accelerometers are DC-responsive that can measure constant acceleration, such as gravity. The major limitations of piezoresistive sensing are the temperature-sensitive drift and the lower level of the output signals [114]

Piezoelectric accelerometers

In a piezoelectric accelerometer, the sensing element bends due to applied acceleration which causes a displacement of the seismic mass, and results in an output voltage proportional to the applied acceleration. Piezoelectric accelerometers are, however, unable to respond to the constant component of accelerations [114]. Although piezoelectric accelerometers do not respond to constant acceleration, their major advantage is that no power supply is required, aside for data storage, resulting in a considerable reduction in size and weight of the device [117,351].

Differential capacitive accelerometers

The displacement of the proof mass in an accelerometer can be measured capacitively. In a capacitive sensing mechanism, the seismic mass is encapsulated between two electrodes. The differential capacitance is proportional to the deflection of the seismic mass between the two electrodes. The advantages of differential capacitive accelerometers are low power consumption, large output level, and fast response to motions. Better sensitivity is also achieved due to the low noise level of capacitive detection. Furthermore, differential capacitive accelerometers also have DC response [114]. Currently this kind of accelerometer has widely been used in most applications, especially in mobile and portable systems and consumer electronics, and can be particularly useful in detecting human movement [114].

Accelerometry is the most commonly used objective method of physical activity assessment in children and adolescents and it has greatly increased in popularity relative to other objective methods in all age groups [352]. A review of physical activity measurement in preschool children reported that 63% of monitoring devices used were accelerometers, mainly the ActiGraph [136].

Accelerometry issues

Discrepancies in accelerometer-intensity thresholds

Currently, the main challenge is to achieve consistency on accelerometer cut points that are representative of children's physical activity [353,354]. Inconsistent accelerometer-intensity thresholds limit between study comparability [355]

Problematically reaching a consensus on the most appropriate thresholds to use is challenging [353] making physical activity data analysis and interpretation difficult. It has been asserted that the comparison of already available thresholds rather than the introduction of new ones may help reduce this inconsistency [356]. Further, although one size fits all accelerometer thresholds can be useful for predicting the time spent in different activity intensities, they are not as precise on an individual level [357]. Large variation in activity counts for children walking at standardized speeds has been reported [358]. Accelerometer activity counts have been shown to range from around 400 up to 2600 counts per minute during walking at 4 $km \cdot h^{-1}$ and from 1000 to 5000 counts per minute during walking at 6 $km \cdot h^{-1}$. The coefficient of variation for activity counts ranged from 21-40%. This high variation precludes the prediction of energy expenditure or classification of intensity and undermines the use of generic cut points for moderate or vigorous physical activity.

Epoch length

For children, the epoch length (a user specified averaging period for time) implemented whilst utilising and accelerometer is an important consideration when describing physical activity due to the intermittent nature of their activity and the typically short bouts [124]. It has been suggested that an even greater amount of daily moderate intensity activity relative to the existing physical activity guidelines for children and youth (Strong et al., 2005) may be important to prevent risk factors related to obesity in childhood [359]. However, in Andersen, et al. [359] this study physical activity was measured using one minute epochs and accelerometer thresholds for ≥moderate intensity activities were based on 3 METs. The evidence suggests that children accumulate physical activity in short bouts throughout the day; therefore the use of one minute epochs can miss short activity bouts and resultantly underestimate moderate to vigorous intensity physical activity [360]. This is because children accumulate vigorous intensity activity in short, sporadic bouts; one minute epochs are too long to capture the majority of these bouts, effectively smoothing out the vigorous activity. A prime example of the potential negative impact of epoch length is shown in Nilsson, et al. [361]. Where 16 children (7 y) wore an accelerometer for four days. Activity data were subsequently analyzed in 5, 10, 20, 40 and 60 second epochs. Using MET prediction equations for 60 second epochs [362] and applying scaling factors for cut-points equivalent to 5, 10, 20 and 40 seconds, significant epoch effects were discovered for estimated time in vigorous and above vigorous intensity physical activity [361]. Longer epochs underestimated time in vigorous and above vigorous intensity activity in these children. Many commercial devices have sufficient memory to measure physical activity using short epochs over a prolonged period of time. Therefore, the use of a short epoch will allow time in vigorous and above vigorous intensity activity in children to be captured so that a more accurate representation of the activity pattern may emerge.

Wear time, weekday versus weekend days

For field-based research, when activity is being measured over a prolonged period of time, it is important that the data processing and storage capabilities of the accelerometer are sufficient. Between four to nine days of monitoring are required to obtain a representative level of activity for children [360]. Since differences have been reported for weekday and weekend activities [360], a combination of weekdays and weekend days should be included in physical activity measurement. In a cohort of children and adolescents, seven days of monitoring demonstrated acceptable estimates of daily moderate to vigorous physical activity (ICC = 0.76-0.86) and accounted for differences in activity on weekdays and the weekend [363].

Fundamental issues

Traditional accelerometer devices predominantly store a summary measure of the raw acceleration signal, termed an “activity count” [40]. A count is, however, a dimensionless unit aimed to be proportional to the average overall acceleration of the human body in a specified period of time [117]. However, this relationship has been questioned due to the restrictive dynamic range of commercial accelerometers, the downstream signal processing and band-pass filtering [34]. Such processing and filtering is designed to remove components of the signal unrelated to human movements [41,217], however high frequency movement and noise information can escape the bandpass filter, which in turn adds unexplained variation in activity counts and incorrectly removes frequencies directly from human movement [35].

There are a plethora of methods that exist to filter and summarise a raw acceleration signal, the choice of which has profound implications on the interpretation of the final output [34,39]. However, as traditional accelerometers are limited in memory and battery capacity to store raw signal data, data processing stages are performed on the device itself, and this process is irreversible once the count has been stored in local memory. This irretrievable conversion prevents re-analysis of the raw accelerometer signal using novel analytics and data processing techniques.

Although a detailed methodology of the signal processing protocol used would be essential to enable replication of empirical data, most manufacturers of accelerometer devices state that pre-processed raw data is proprietary information. This lack of transparency on the calculation of “activity counts” prevents a comparison between different accelerometer brands, or even between versions of the same brand [40,41]. On the other hand “activity counts” derived from a raw accelerometer have high concordance with commercially developed devices ($r=0.93$, $P<0.05$), demonstrating the versatility of utilising the raw accelerometer signal [34].

Using a raw accelerometer signal, where all frequencies related to human movement are included allows novel analyses, such as; pattern recognition, feature extraction, machine learning, cluster analysis and data mining to be undertaken, without violating the Nyquist-Shannon sampling theorem [34,200]. The Nyquist-Shannon sampling theorem specifies that the sample must contain all the available frequency information from the signal to result in a faithful reproduction of the analogue waveform signal. Further, put simply, if the highest frequency component, in Hz, for a given analogue signal is f_{max}, according to the Nyquist-Shannon sampling Theorem, the sampling rate must be at least $^{2}f_{max}$, or twice the highest analogue frequency component. If the sampling rate is less than $^{2}f_{max}$, and/or if all the available frequency information is not available, the signal will not be correctly represented in the digitized output [364,365]. Further, given there is no hidden signal processing, researchers may maintain control and confidence in their outputs. This has led to more widespread use of raw accelerometry and the application of novel analytical techniques.

Accelerometer usage

Posture and Movement Classification

Movement classification using accelerometry-based methodologies has been widely studied. Approaches to movement classification can be threshold-based or achieved using statistical classification techniques. Threshold derived movement classification takes advantage of known knowledge and information about the movements to be classified. It requires a hierarchical algorithm to discriminate between activity states.

A set of empirically-derived thresholds for each classification subclass are required. Kiani, et al. [366] demonstrated a systematic approach to movement classification based on a hierarchical decision tree that allows automatic movement detection and classification. Mathie, et al. [367] further presented a classification framework consisting of a hierarchical binary tree for classifying postural transitions, falls, walking, and other movements using raw acceleration signals. Tilt sensing is a basic function provided by many accelerometers which respond to gravity or constant acceleration and with this capability human postures may be distinguished according to the magnitude of acceleration signals along sensitive axes [114,368]. However, the single-accelerometer approach has been shown to have difficulty in distinguishing between standing and sitting as both are upright postures, although a simplified approach with tilt threshold to distinguish standing and sitting was proposed [368]. Standing and sitting postures can be distinguished by observing different orientations of body segments where multiple accelerometers are attached. For example, two accelerometers can be attached to the upper body and leg to differentiate standing and sitting postures from static activities [369]. Sit to stand postural transitions can be identified according to the patterns of vertical acceleration from a hip or centrally mounted accelerometer [114]. Raw acceleration signals can be used to determine walking and other ambulatory movement by employing frequency-domain analysis [368,370]. Ohtaki, et al. [370] asserted a variance of over 0.02 g in vertical acceleration and a fundamental frequency peak within 1–3 Hz in the signal spectrum specifically identifies walking. Discrete wavelet transform (frequency and time domain analysis) has also been used to distinguish walking on a level ground vs. walking on a stairway [371]. Movement classification using statistical techniques generally utilize a supervised machine learning procedure, which associates a feature of movement to movement states in to predict the observation. An example of some techniques include; *k*-nearest neighbour (kNN) classification [372], support vector machines (SVM) [373], Naive Bayes classifier [374], Gaussian mixture model (GMM) [375] and hidden Markov model (HMM) [376]. Naive Bayes classifier determines activities according to the probabilities of the signal pattern of the activities. In the GMM approach, the likelihood function is not a typical Gaussian (typical bell curve) distribution. The weights and parameters describing probability of activities are obtained by the expectation-maximization algorithm [114]. Transitions between activities can be described as a Markov chain that represents the probability of transitions between different activities. The HMM is applied to determine unknown states at any given time according to known activity features that have been extracted from accelerometry data. After the HMM is trained by example data, it can be used to determine various activity states and transitions.

Estimation of Energy Expenditure

The gold standard for EE estimation is considered to be DLW and direct calorimetry. Though accurate, gas analysers for indirect calorimetry are expensive and they require specialist skills and training to operate. Additionally, isotope analysis and production for DLW method are expensive and are unsuitable for large-scale studies neither do they provide temporal patterning of physical activity [377]. Accelerometers provide an alternative method of estimating EE in a free-living environment. Physical activity Energy expenditure is better predicted from the anterior-posterior direction of the accelerometer signal [132], although the vertical acceleration is most sensitive to a majority of activities like walking or running. The signal integral of triaxial acceleration outputs has been shown to have linear relationship with the metabolic energy expenditure [133]. Commercial accelerometers follow the same principles and convert raw acceleration signal into activity counts over an epoch. The activity counts represent the estimated intensity of measured activities during each time period and subsequently compared with the DLW method [134] or indirect calorimetry to estimate the energy expenditure [135]. Factors affecting the accuracy of EE estimation using accelerometry include; the location and attachment of the accelerometers, external interference, signal noise ratio, and certain types of activity particularly intense intermittent activity performed in a free-living environment. Sensor attachment to a central position is preferred for EE estimation because the trunk represents is closest to the centre of mass. Further, accelerometers attached to this portion of the body are generally less responsive to the gravitational effect [133]. Conversely, hip mounted accelerometers are unable to measure upper limb movement or gait and have inaccurate EE estimation when the participants carry different loads during activity [367]. Further, EE during walking may be inaccurately estimated when the locomotion is not horizontal, e.g., slope climbing and walking up and downstairs can hinder accurate estimation [114].

Fall detection, balance and the frequency component

A further example of accelerometry use that has expanded is in fall detection and balance assessment. Fall-related injuries can result in serious trauma, deleteriously affecting the health and functional status of elderly people, leading to living dependence and higher risk of morbidity and mortality [114]. Falls can be conceptualised as a rapid postural change from upright to reclining position to ground, [378]. One of the first studies to monitor fall detection using accelerometry was Williams, et al. [379], and a fall detector was presented after a number of pilot studies [380]. More recently, Dobkin, et al. [381] and Aziz, et al. [194] successfully measured physical activity, sedentary behaviour and falls using accelerometers in older adults or those with impaired ambulation. However, they noted problems arose when using the same approach in highly transitory activities and when detecting falls that were a result of syncope. Lindemann, et al. [382] has also evaluated fall detection using a device that was fixed behind the ear. Two accelerometers were orthogonally placed in the device such that accelerations along all the sensitive axes could be measured. In fall detection there is generally some implemented thresholds such that if certain axes fall below a specific 'g' value, it is registered as a fall [382]. Balance control or postural stability of the body while standing or during ambulation has been regarded as an important predictor of risk of falling in the elderly [383]. Lord, et al. [384] proposed the physiological profile assessment (PPA), which adopts postural sway as one of the six tests for screening fall risk and can be measured using a sway meter that records body displacement at waist level. Force plate or pressure sensors can also be used to record the trajectory of centre of pressure which is linked to postural sway [385]. Postural sway can also be measured by using accelerometers [386]. Triaxial accelerometers have been used to obtain the postural sway on a level ground [387], with the known height from the sensor to the ground, and the sensor output displaying the tilt angle, trigonometric calculation can be applied to obtain the trajectory in the anterior-posterior and medio-lateral axes projected on a level plane. The advantage of this technique is that an accelerometer is very sensitive to the different test conditions and is easily transportable. Studies also showed a moderate correlation (r=0.5-0.68) between trunk acceleration and centre of pressure pattern [388]. Detailed gait parameters have been utilised to assess balance control, functional ability, and risk of falling. Gait parameters during free walking can be measured by using accelerometers and the raw signal can be used to identify heel strike [389], gait cycle frequency, stride symmetry and regularity [390]. Aminian, et al. [391] noted that measurement of temporal parameters of gait may be measured successfully with the addition of a miniature gyroscope. Moe-Nilssen, et al. [174] estimated gait characteristics of the subjects during controlled walking, using a triaxial accelerometer affixed to the lower trunk, the raw acceleration signals were subsequently analyzed using an autocorrelation procedure to obtain cadence, step length, and gait regularity and symmetry. Gait features between young and elderly subjects have been compared using accelerometry data and has been shown that vector magnitude values of accelerations obtained from the pelvis and head (vertical component) of elderly subjects are smaller compared to younger subjects [392,393]. Elderly subjects demonstrated slower velocity, reduced step length, and larger step timing variability during both walking on level and irregular surfaces. A further technique applied to assess balance control is the analysis of frequency and harmonic content of the acceleration signal. The harmonic ratio has been proposed as a measure of smoothness of walking, and is defined as the ratio of the summed amplitudes of the even-numbered harmonics to the summed amplitudes of odd-numbered harmonics both obtained from finite Fourier transform [18]. Older people with elevated risk of falling have been shown to exhibit lower harmonic ratio [18,393]. Accelerometers have also been used to assess characteristics such as ambulation smoothness, control, balance and rhythmicity (how cyclical a movement is) [18,19]. These characteristics are retrievable using the frequency and harmonic content of the accelerometer signal, based upon harmonic theory to examine the symmetry within a movement by exploiting the periodicity of the signal [295,296]. The measured accelerations for each movement can be analyzed in the frequency domain through a well-established technique of Fourier analysis [394]. These fundamental characteristics of the raw signal reveal details surrounding gait and movement [18,218,257,297,299,337].